AN ECONOMETRIC INVESTIGATION OF THE RELATIONSHIP BETWEEN THE PRICE OF OIL AND U.K. MACROECONOMIC PERFORMANCE

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DECLARATION

Whilst registered as a candidate for a Ph.D., I have not been registered for any other research award. The results and conclusions embodied in this thesis are the work of the named candidate and have not been submitted for any other academic award.

Robert Gausden (April 2013)

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LIST OF ABBREVIATIONS

Abbreviation	Full
3SLS	Three-Stage Least Squares
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
BIC	Schwarz Bayesian Information Criterion
CGP	Cambridge Growth Project
CPI	Consumer Price Index
CUBS	City University Business School
DF	Dickey-Fuller
E.S.R.C	Economic and Social Research Council
EMF	Energy Modeling Forum
GARCH	Generalised Autoregressive Conditional Heteroskedastic
GLS	Generalised Least Squares
HMT	Her Majesty’s Treasury
HQIC	Hannan-Quinn Information Criterion
KPSS	Kwiatkowski, Phillips, Schmidt and Shin
LBS	London Business School
LPL	Liverpool University
LR	Likelihood Ratio
LTIR	Long-term rate of interest
MAIC	Modified AIC
MBIC	Modified BIC
MMB	Macroeconomic Modelling Bureau
NIESR	National Institute of Economic and Social Research
NOPI	Net oil price increase
OLS	Ordinary Least Squares
PINF	Price inflation
PP	Phillips-Perron
PPI	Producer Price Index
RAC	Refiner acquisition cost

REER	Real effective exchange rate
ROILP	Real price of oil
RW	Real wages
S.E.	Standard error of the regression
S.I.C	Standard Industrial Classification
S.S.R.C.	Social Science Research Council
SOPD	Scaled oil price decreases
SOPI	Scaled oil price increases
SUR	Seemingly Unrelated Regressions
TB	Short-term rate of interest
VAR	Vector Autoregressive
VECM	Vector Error Correction Model
VMA	Vector Moving Average

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ABSTRACT

The objective of this thesis is to conduct an econometric investigation of the relationship between the price of oil and U.K. macroeconomic performance. For this purpose, quarterly seasonally-adjusted time series have been collected which extend from 1972 to 2008. Empirical results are obtained from the estimation of unrestricted and restricted vector autoregressive models. The conclusions which are reached in this study are founded upon both within- and post-sample analyses of the data.

A considerable amount of research has already been devoted to the subject of the relationship between the price of oil and macroeconomic performance. Within the empirical literature, much attention has been paid to whether the macroeconomic consequences of an increase in the price of oil are symmetrical to those of a decrease. However, a largely neglected issue has been whether or not the effects of an oil price shock are subject to variation over time. The fundamental contribution which is made by this thesis is to rectify this situation through applying suitable extensions to two existing vector autoregressive models.

From the empirical analysis which is subsequently undertaken, it is apparent that spurious results can arise from failing to allow for both the change in the status of the U.K. to a significant exporter of crude oil and the reduction in the intensity with which this commodity is utilised in the production process. In particular, without the recommended augmentations, the importance of past movements in the price of oil to macroeconomic performance would be seriously understated.

CONTENTS

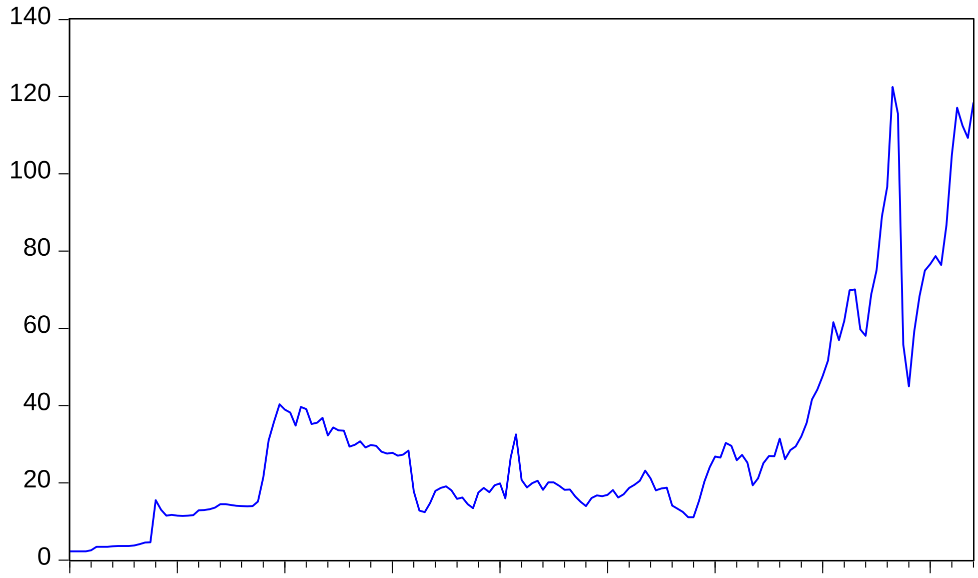
CHAPTER ONE

INTRODUCTION

The objective of this thesis is to perform an econometric investigation of the relationship between the price of oil and U.K. macroeconomic performance. In order to achieve this aim, methods are relied upon which permit only a modest role to economic theory. More specifically, conclusions are reached from having undertaken unrestricted vector autoregressive modelling, a cointegration analysis, and estimation of vector error-correction systems.

Given the topic of this thesis, an obvious starting point is the presentation of data on the price of oil. Thus, Figure 1.1, below, shows in diagrammatic form the quarterly time series on the price of Brent crude oil, expressed in U.S. dollars, which extends from 1970q1 to 2012q1.[1]

Figure 1.1: Price of Brent Crude Oil, 1970q1-2012q1



[1] The source of this data series is *International Financial Statistics*, June 2012, which was accessed on-line on 20th July 2012.

Over this interval, the average price of Brent crude oil was $30.10 per barrel. The minimum value was $2.23 per barrel, which was recorded right at the start of the period. The largest value can be observed to be $122.48 per barrel, which corresponds to 2008q2. The data period, 1970q1-2012q1, covers 169 quarters. In 6 of these, there occurred no change in the price of oil. Distributed over the remaining 163 quarters were 96 increases and 67 decreases in the price of oil.

Between 1970q1 and 2012q1, the average quarterly percentage change in the price of oil was 4.03 per cent. On four occasions, the quarterly growth rate managed to surpass 40 per cent. By some distance, the largest quarterly rise in the price of Brent crude oil (= 236.96 per cent) took place in 1974q1. As a consequence of the support that was given by the U.S. and European nations to Israel in the Yom Kippur war,[2] which commenced in October 1973, an embargo was imposed by the Arab states which restricted the shipment of oil to western countries. On 23rd December 1973, the oil-producing countries in the Gulf region decided to more than double the posted price for Saudi Arabian light crude oil from the beginning of the subsequent year.

In 1979q1 and 1979q2, the price of Brent crude oil increased by 41.10 and 44.70 per cent, respectively. These upward movements were connected to the loss of oil exports from Iran, following the Islamic revolution which occurred in this country. Finally, in 1990q3, the price of oil rose by 66.02 per cent. This development was related to the invasion of Kuwait by Iraqi troops on 2nd August 1990. Two days' later, the European Community, the U.S. and Japan imposed an embargo on the imports of oil from both of these two countries.

[2] The conflict between the Arabs and the Israelis in 1973 has become known as the Yom Kippur war, as it was initiated by an attack on Israel by Egyptian and Syrian military forces on the Day of Atonement, the holiest day in the Jewish calendar.

Economic theory maintains that an increase in the price of oil exerts a significant effect on a developed economy. The consequences of a rise in the price of oil are transmitted through both supply and demand channels. Either directly or indirectly, there is a dependence upon oil in the production process. Thus, given a hike in the price of oil, it becomes more expensive to produce a unit of output. In the context of a conventional diagram of aggregate supply and aggregate demand, the aggregate supply schedule shifts upwards, thereby creating a higher equilibrium price and a lower equilibrium quantity of output. On the basis of the upward movement in the price level, the increase in the price of oil may be described as having an inflationary impact on the macroeconomy.

It can be added that a (perceived permanent) rise in the price of oil provides a firm with an incentive to acquire machinery which is more fuel efficient. However, if the firm lacks the funds to purchase the new machinery then its profits will be damaged, which reduces its scope to undertake future investment. A lack of investment will have immediate consequences for demand in the economy. Furthermore, it will restrict the long-term rate of growth of output.

With respect to the demand side of the macroeconomy, an increase in the price of oil operates in the manner of a tax which is imposed on households and firms. The assumption is made that the domestic country is an importer of oil. Consequently, when the oil price rises, a transfer of funds takes place from the home nation to the relevant oil-exporting countries. Hence, there is less income available to households and firms within the home country for expenditure on domestically-produced goods and services. In terms of the diagram of aggregate demand and aggregate supply, the demand schedule shifts to the left, in so doing, lowering the equilibrium level of output. Thus, the increase in the price of oil may be regarded as having a deflationary impact on the macroeconomy.[3]

Of course, the negative effect on demand would be weaker were the oil-exporting nations to devote at least part of their increased revenues towards the purchase of goods and services which are produced by the domestic country. There is also the potential for the oil-exporting nations to use their surplus funds to buy financial assets which are available for sale in the domestic country. This form of foreign investment would serve to suppress interest rates, thereby stimulating expenditure by firms and households.

With reference to Figure 1.1, over the interval, 1970q1-2012q1, there have been three occasions on which the quarterly percentage decrease in the price of oil has exceeded 30 per cent. In 1986q1, there occurred a fall of 37.27 per cent. This was followed by, in 1991q1 and 2008q4, reductions of 36.23 and 51.66 per cent, respectively.

On the basis of the theory which has been presented, above, a decline in the price of oil would be expected to exert a positive influence upon output by promoting downward and rightward shifts of the aggregate supply and aggregate demand schedules, respectively. However, reasons have been offered in the literature for why

[3] An alternative demand-side analysis focuses upon the rise in the general price level that follows from an increase in the price of oil. Without any accommodating change in the supply of money, there occurs a fall in real money balances. In the context of an IS/LM diagram, the LM schedule shifts to the left, thereby raising the equilibrium rate of interest and lowering the equilibrium level of income. Assuming a lack of flexibility of wages, real output decreases.

the beneficial effect on the macroeconomy of a decrease in the price oil may not match the harmful impact of an oil price rise.

One argument which has been forwarded is that any movement in the price of oil (either upward or downward) will stimulate a reallocation of resources between different sectors of the economy.[4] For example, a decrease in the price of oil will redirect resources away from industries that do not place heavy reliance upon oil or are responsible for its production towards those that make intensive use of this commodity. However, there is a recognition that the desired sectoral realignment is difficult to achieve in the short run. Hence, there may occur a significant period over which capacity is underutilised and unemployment exceeds its equilibrium.[5]

It has also been suggested, by, for example, Pindyck and Rotemberg (1982), that either an increase or a decrease in the price of oil will be detrimental to the growth of output, by virtue of creating increased uncertainty. When the future costs or revenues of firms are unpredictable, an incentive is received to postpone taking investment decisions. If such a hypothesis is to be accepted, then, for the purpose of determining macroeconomic performance, the volatility that is displayed by the price of oil would seem to be of greater relevance than the direction of its movement.

A change in the price of oil will motivate a firm to adjust the size of its capital stock. In particular, if the price of oil decreases then the firm will seek to expand the size of

[4] This has become known as the sectoral-shifts hypothesis.
[5] Loungani (1986) sought to test the sectoral-shifts hypothesis, using quarterly data on twenty-eight industries in the U.S. over the interval, 1947-1982. More specifically, he attempted to explain the behaviour of the aggregate unemployment rate through constructing a regression equation which included a dispersion index that measured the variability in employment growth which resulted from differential impacts of oil price shocks across industries.

its capital stock. In the event of an increase in the price of oil, the firm will pursue the objective of a contraction. In this context, asymmetrical effects of a rise and a fall in the price of oil will result if it is straightforward to cease to utilise existing resources, compared to the logistical problems which are encountered in installing new equipment and machinery.

The view has also been expressed that the short-term responses of output to an increase and a decrease in the price of oil will not be commensurate to one another for the reason that firms possess an incentive to act with different degrees of haste to a rise and a fall in the price of a factor of production. More specifically, should the use of a factor become more expensive then suitable adjustments would take place relatively rapidly if the survival of the organisation is being threatened. In contrast, should the factor input become cheaper, there would be less pressure on a firm to modify its production methods, given that, with existing arrangements in place, profits would still be enhanced.

In an empirical study, Huntington (1998) sought to investigate the possibility that asymmetrical effects on macroeconomic activity of an increase and a decrease in the price of crude oil were derived from how a change in the price of oil passes through the energy system. Consequently, he conducted an analysis, using annual data on the U.S., in order to establish the connections between the behaviour of the price of crude oil, the price of refined petroleum products, and the wholesale price of fuel and power.

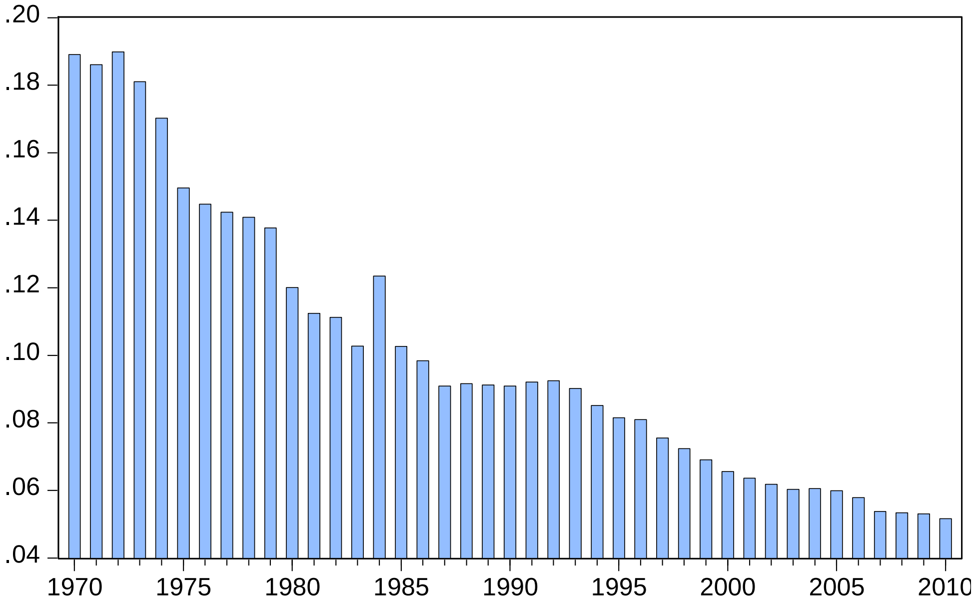
Having performed regressions over the period, 1949-1993, Huntington found that the price of refined petroleum products responded more rapidly to an upward than a downward movement in the price of crude oil. Additionally, in relating the price of fuel and energy to that of refined petroleum products, at a conventional level of significance, it was not possible to reject the null hypothesis of symmetry.

Huntington also examined econometrically the responsiveness of output growth to changes in each of the three energy price variables. He discovered that for neither the price of fuel and power nor the price of refined petroleum products did the data contradict the notion of symmetry. In contrast, the evidence supported the existence of asymmetrical effects of an increase and a decrease in the price of crude oil. However, this result was reversed following the exclusion from the analysis of data corresponding to 1987.

As the literature review which is conducted in Chapter Two of this thesis will demonstrate, much effort has been contributed towards exploring empirically the issue of whether or not the macroeconomic consequences of a rise in the price of oil are symmetrical to those of a fall in its price. Curiously, perhaps, far less attention has been devoted towards examining whether or not the macroeconomic implications of an oil price shock have remained constant over time. In connection with the U.K., this would seem to be an especially important matter to address, given that, since the early 1970s, not only has the country's dependence upon crude oil reduced but also the U.K. acquired the status of a producer and an exporter of crude oil.

Figure 1.2, below, shows, from 1970 to 2010, the ratio of the U.K.'s consumption of crude oil to its G.D.P.. The consumption of oil is measured in terms of million tonnes, while the data on G.D.P. are contained in the form of 2009 prices and are expressed in £billion.[6]

Figure 1.2: Ratio of U.K.'s Consumption of Oil to Gross Domestic Product



The graph indicates that, from 1970 to 2010, the size of the ratio of the U.K.'s consumption of crude oil to its G.D.P. fell from 0.189 to 0.052. This represents a reduction of 72.7 per cent. The steepest annual decline occurred in 1975 (12.1 per cent). Also, it can be observed that, from 1993 to 2010, the value of the ratio decreased in every year, with the exception of 2004. The largest increase in the ratio is associated with 1984 (= 20.2 per cent), which can be attributed to the industrial action that was taken by the National Union of Mineworkers during that year.

[6] Data on G.D.P. (codename ABMI) were accessed from the website of the Office for National Statistics. The series on oil consumption was obtained on-line from B.P.'s *Statistical Review of World Energy 2011*. The data were retrieved on 20th July 2012.

Figure 1.3: U.K.'s Exports and Imports of Crude Oil (Thousand Tonnes)

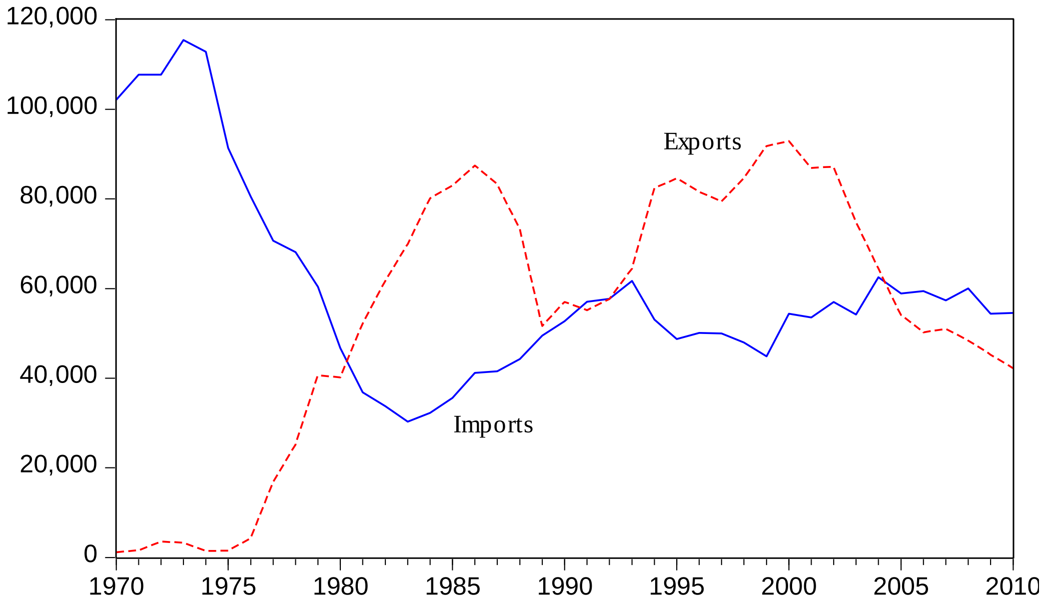


Figure 1.3, above, presents annual data on the U.K.'s exports and imports of crude oil over an interval which extends from 1970 to 2010.[7] The graph reveals that, from a starting position of virtually zero in 1970, the U.K.'s exports of crude oil ascended to a peak of 87,437 thousand tonnes in 1986. Having dropped to as low as 51,664 thousand tonnes in 1989,[8] there then occurred another rise to an overall maximum for the period of 92,917 thousand tonnes in 2000. Finally, from 2000 to 2010, the quantity of crude oil that is exported by the U.K. can be seen to have declined by 54.6 per cent.

With the emergence of the U.K. as a producer of oil, the quantity of imports fell from 115,472 thousand tonnes in 1973 to 30,324 thousand tonnes in 1983. Following this low point, there occurred ten successive increases, such that, in 1993, imports of

[7] The data source is Table 3.1.1 of the *Digest of U.K. Energy Statistics*, which was accessed on-line on 20th July 2012.

[8] This reduction is connected to the fire on the North Sea oil rig, the Piper Alpha, which occurred on 6th July 1988. At the time of the disaster, this platform was responsible for approximately ten per cent of North Sea oil and gas production.

crude oil had reached 61,701 thousand tonnes. Finally, from 1994 to 2010, there appears to have been relatively little variation in the quantity of imports, with all of the values lying within a range of less than 18,000 tonnes.

With regard to a conventional diagram of aggregate demand and aggregate supply, it has already been mentioned that, in the situation of an increase in the price of a factor input, such as oil, the aggregate supply schedule shifts upwards. However, as there occurs an improvement in the productivity of the factor, a rise in its price of a given magnitude will be associated with a less substantial upward movement of the aggregate supply curve.

Earlier, in the same context, reference was made to an increase in the price of oil having the effect of shifting the aggregate demand schedule to the left, on account of the outward flow of funds towards the oil-exporting countries and the reduced income being available for expenditure on goods and services that are produced in the domestic country. However, as the dependence upon imported oil falls, an increase in the price of this commodity will result in a less considerable movement of the aggregate demand curve. Indeed, should the domestic country achieve the status of a net exporter of oil then the aggregate demand schedule will be repositioned to the right of its previous location.

Ignoring the aforementioned developments, when analysing the relationship between the price of oil and U.K. macroeconomic performance, has the potential to deliver spurious inferences. For example, in 1974, when there occurred the most dramatic increase in the price of crude oil, the U.K. consumed 105.3 million tonnes of oil, which represented 17.0 per cent of the corresponding figure for G.D.P., expressed in £billion and 2009 prices. Additionally, in the same year, imports of crude oil exceeded exports by 98.2 million tonnes. In contrast, in 1986, when there was witnessed one of the most substantial falls in the price of crude oil, the U.K. demanded only 77.4 million tonnes of oil, which constituted 9.84 per cent of G.D.P.. Also, in this year, exports of crude oil managed to surpass imports by 46.2 million tonnes.

On account of the structural developments that have been identified in connection with the U.K. economy from 1974 to 1986, it follows that if the same percentage change in the price of oil had been experienced in both of these years then the resultant shifts of the aggregate supply and aggregate demand schedules would have been far less pronounced in 1986. As a consequence, the macroeconomic effects of any form of oil price shock would have much weaker in 1986 than 1974. Thus, in the course of econometric modelling, should a lack of attention be paid to the aforementioned improvements then a risk would possibly be incurred of erroneously drawing the inference that a decrease in the price of oil, ‘under any circumstance’, possesses limited implications for U.K. macroeconomic performance.

Through having taken place in the context of a model of aggregate supply and aggregate demand, the discussion has focused upon the relationship between the price of oil, the general price level and the level of real income or output. However, it should be respected that, when the status of the U.K. altered to being a producer and an exporter of crude oil, the nature of the association between the price of oil and the U.K.’s exchange rate was possibly disturbed. Also, given a situation in which the currency of the U.K. appreciates in response to an increase in the price of oil,[9] the monetary authorities would possibly be able to control price inflation with lower rates of interest prevailing than otherwise.

Hence, the principal contribution which is made by this thesis is to allow for key structural changes which have occurred to the U.K. economy in the process of modelling the relationship between the price of oil and U.K. macroeconomic performance. Within the chosen econometric system, by explicitly catering for some fundamental sources of instability, the intention is to be able to attach greater validity to the results which are generated.[10]

The thesis proceeds by, in Chapter Two, conducting a review of relevant empirical studies. It should be appreciated that this chapter does not seek to make reference to every past investigation that has occurred of the relationship between the price of oil and macroeconomic performance. Rather, its approach is far more selective, choosing to consider only those contributions which have influenced the econometric analysis which is undertaken in this thesis.

Empirical research necessitates that certain fundamental issues be addressed, for example, the framework that is to be used as the basis for the study and the variables which are permitted to enter this. It subsequently requires decisions to be taken with

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[9] The so-called 'Dutch disease' maintains that the discovery by a country of a natural resource will have a negative effect on the economic performance of its traditional industries, which is transmitted via the means of an appreciating currency

[10] It would be inappropriate to claim that 'all' forms of instability are accounted for in the respective econometric model. For example, no consideration is given to possible changes in the manner of wage determination, as the labour market in the U.K. has become more flexible over the past forty years. Also, no attention is paid to different strategies that have been adopted in an attempt to control price inflation.

respect to the span and the frequency of the data, and a view to be formed of whether or not seasonal adjustment would be beneficial. Furthermore, a recommendation is sought concerning a broad approach towards assessing the suitability of an econometric model, while specific statistical tests should be proposed for implementation. Chapter Three thus presents justifications for the key choices which are made in the thesis, while Chapter Four details the results of applying the methodology that has been advanced. In particular, it contrasts the findings which follow from the estimation of four different unrestricted vector autoregressive models.

Chapter Five returns to a consideration of methodological issues. More specifically, an explanation is offered for proceeding to undertake cointegration analysis and to estimate a vector autoregressive model which incorporates long-run restrictions. Reference is made to system tests of cointegration and a distinction is drawn between different types of vector error-correction model. Subsequently, Chapter Six reports the results which are obtained from the application of the advocated procedures and the estimation of the vector error-correction models. Finally, in Chapter Seven, an attempt is made to summarise the principal findings of the thesis and to draw some conclusions. Additionally, reflection is given to the possible limitations of the analysis that has been conducted and the potential for future research in this area.

CHAPTER TWO

REVIEW OF EMPIRICAL STUDIES

The objective of this chapter of the thesis is to provide a review of empirical studies which have sought to investigate the relationship between the price of oil and macroeconomic performance. The chapter is divided into four broad parts. The first section summarises results that have been obtained from simulations which have been conducted in conjunction with structural macroeconometric models. The second section discusses the significant contribution which has been made by and the influence of James D. Hamilton. Next, attention is directed towards econometric analyses which have been founded upon the construction and estimation of vector autoregressive (VAR) models. Finally, the focus is upon selected academic papers, each one of which has been concerned with the effects of oil price shocks on the U.K. economy.

2.1 Structural Macroeconometric Models

2.1.1 Conclusions of the Energy Modeling Forum Working Group

Given the stated aim of this element of the thesis, a reasonable starting point would seem to be a consideration of the first chapter in the book that was edited by Hickman, Huntington and Sweeney (1987), entitled *Macroeconomic Impacts of Energy Shocks*. The first chapter in this volume represents a report on the conclusions that were reached at four meetings of the seventh Energy Modeling Forum (EMF) working group, which were held over an eighteen-month period during 1982 and 1983. The working group comprised approximately forty macroeconomic modellers and potential model-users from universities, the business community and government. The prime task of the working group was to compare predictions that were produced by fourteen prominent macroeconomic models. Specifically, these forecasts were of the short-to-medium-term macroeconomic consequences of different changes in the price of energy.

The macroeconomic models participating in this exercise consisted of virtually all of the widely used U.S. models, together with a Canadian energy-economy model and two models which allowed for linkages between major countries. The models are listed below, having been divided into two groups. Group 1 includes large systems of equations that have been used to produce forecasts of the U.S. economy over a three-to-five-year horizon. Group 2 contains relatively small macroeconomic models, representing many diverse perspectives.

Group 1

Bureau of Economic Analysis quarterly econometric model

Chase quarterly macroeconomic model

Data Resources Incorporated quarterly model

LINK system[11]

Michigan annual econometric model

M.I.T. - PENN. - S.S.R.C. model

Wharton quarterly model

[11] The LINK model allowed for linkages between thirty-two major economies.

Group 2

Claremont Economics Institute domestic model	(incorporating rational expectations and monetarist principles)
Federal Reserve Board multi-country model	(which allowed for trading relationships between Canada, Germany, Japan, the U.K. and the U.S.)
Hickman-Coen annual growth model	
Hubbard-Fry model	(including explicit modelling of the world oil market)
MACE model	(a model of the Canadian economy, containing substantial detail on the energy market)
Mork model	(featuring explicit modelling of the world oil market, rational expectations and short-run rigidities in the labour and capital markets)
St. Louis Federal Reserve Bank model	(a monetarist system)

Simulations were performed in conjunction with each of the fourteen models for the purpose of predicting the macroeconomic consequences of the hypothetical future energy price shocks which are indicated below:

(i) a 50 per cent increase in the nominal price of imported oil;

(ii) a 20 per cent reduction in the nominal price of imported oil;

(iii) an 80 per cent increase in the price of wellhead natural gas;

(iv) a 20 per cent increase in the nominal price of imported oil.

With reference to these four shocks, it was assumed that each change in price is maintained over a four-year horizon. Also, the increase in the price of gas was chosen as one form of disturbance such that it was possible to examine whether or not the macroeconomic effects of an energy price shock are sensitive to the origin of the energy resource. Under the baseline conditions that were employed in this study, expenditure on wellhead natural gas amounted to only twenty-five per cent of the total that was spent on imported oil. Hence, an increase of eighty per cent in the price of gas was considered to be financially comparable to an increase of twenty per cent in the world price of oil.

A fifty per cent increase in the price of imported oil involved a movement from $36 to $54 per barrel. The four-year cumulative loss in real G.N.P. and purchasing power that was predicted ranged from $246.0 billion (1983 prices), produced by the Hickman-Coen model, to $747.1 billion, obtained from the Mork model.[12] The average predicted loss was $452.4 billion,[13] which constituted approximately 3.2 per cent of the cumulative baseline real G.N.P..

[12] The Michigan, Claremont and St. Louis models were unable to predict terms-of-trade losses. Hence, they were excluded from this comparison.
[13] Ignoring the loss that was forecast by the LINK model.

Of this average predicted loss, 72.5 per cent was attributable to real G.N.P.. Purchasing power thus accounted for the remainder. The decline in purchasing power emanated from the price of imported oil rising more rapidly than the price of U.S. output. As a consequence, an increased volume of exports was required to finance expenditure on a given quantity of imported oil. By implication, a smaller proportion of U.S. output was available for internal use.

For each of real G.N.P., the implicit G.N.P. deflator and the unemployment rate, median results were calculated, founded upon the predictions of the U.S. macroeconomic models.[14] These results showed that, in the second year of an oil price of $54 per barrel, real G.N.P. is 2.90 per cent less than it would have been in the absence of a change in the price of oil. Also, the rate of unemployment is 1.21 percentage points higher and the domestic price level is 2.02 per cent greater than would have been the case had no oil-price shock occurred.

The predicted macroeconomic consequences of the other three energy price shocks were examined, after which it was possible to reach the following conclusions:

- the second-year effects on real G.N.P. and the G.N.P. deflator are virtually proportional to the extent of the increase in the price of imported oil;[15]

[14] Ignoring the predictions that were produced by the LINK model.
[15] Specifically, the following relationships were derived from the median results corresponding to a fifty per cent rise in the price of oil. For every movement upwards of $5 per barrel in the price of oil, there occurs a loss in real G.N.P. of 0.8 per cent and an increase in the implicit G.N.P. deflator of 0.6 per cent.

- in the presence of considerable unemployment, a sudden reduction in the price of imported oil has macroeconomic effects that are opposite in direction but approximately equal in magnitude to those that are produced by a sharp increase of the same percentage;
- the consequences for real G.N.P. of an energy price shock are largely independent of whether the energy originates from the U.S. or is imported.[16]

2.1.2 Simulations performed by the E.S.R.C. Macroeconomic Modelling Bureau

The Macroeconomic Modelling Bureau (MMB) was established by the Social Science Research Council (S.S.R.C.) at the University of Warwick in September 1983.[17] The MMB was set up with an agenda which included providing improved access to models of the U.K. economy. Another goal was to increase the accountability of organisations that published forecasts which were based upon these macroeconomic models.

Upon its construction, the MMB aimed to undertake annually an examination of the properties of U.K. macroeconomic models and an analysis of the forecast performance of each. Also, the intention was, every year, to focus upon at least one aspect of these models. In its first review of models of the U.K. economy, the MMB devoted special attention to the treatment of the labour market in the models.[18] As part of the second

[16] However, as explained earlier, an increase in the price of imported energy reduces purchasing power. Hence, the total economic loss resulting from an energy price rise is greater when the energy is imported.
[17] The S.S.R.C. was the precursor to the Economic and Social Research Council (E.S.R.C.).
[18] See Wallis *et al*. (1984), Chapter 4.

review, detailed consideration was given to the modelling of North Sea oil.[19] Simulations were performed, having allowed for changes in different variables entering the North Sea oil sector of the respective model. One of the shocks that was applied took the form of a twenty-five per cent reduction in the price of oil. The predictions that were generated are discussed below after a brief description of each of the models has been provided.

The macroeconomic models which were compared by the MMB in its second review consisted of the model of Her Majesty's Treasury, as well as the models belonging to institutions that received financial support from the E.S.R.C.. *Circa* 1985, there were five models of the U.K. economy that were being developed with the aid of E.S.R.C. funding. These were the models of the Cambridge Growth Project, the City University Business School, Liverpool University, the London Business School, and the National Institute of Economic and Social Research. The versions of the six models that were subject to scrutiny were those that became available in late 1984 or early 1985. Some of the salient features of the models are shown below.

[19] See Wallis *et al*. (1985), Chapter 5.

Quarterly Models	
London Business School (LBS)	The model adopts the income-expenditure framework. The main influence of money is via the behaviour of the exchange rate.
National Institute of Economic and Social Research (NIESR)	The model adopts the income-expenditure framework. It is, in the main, a quantity-adjustment model.
Her Majesty's Treasury (HMT)	The model adopts the income-expenditure framework. It contains a detailed treatment of the public sector. The model features both sluggish price adjustment and quantity adjustment.
Annual Models	
Cambridge Growth Project (CGP)	A Leontief input-output model is embedded within a conventional macroeconomic model. The model covers 39 industries and commodities. Real flows are emphasised, rather than monetary or financial flows.

(continued)

City University Business School (CUBS)	The model gives consideration to the determination of the supply of output. It contains only 10 behavioural equations.
Liverpool University (LPL)	The model's overall structure is defined by economic theory. It is a 'new classical' model, incorporating rational expectations and the assumption of rapid price adjustment.

The only one of the U.K. models in which North Sea oil is not represented is the LPL model. In all of the other models, both the price and output of oil are treated as exogenous. In each of HMT, the NIESR and CUBS models, a change in the price of oil has an effect on the demand side of the economy through the mechanism of the exchange rate. More specifically, in HMT model, the real value of North Sea oil production is partly responsible for the long-run equilibrium exchange rate. In the NIESR model, the real value of domestic oil reserves is one of the explanatory variables entering its exchange rate equation. In the CUBS model, a change in the relative price of oil alters the U.K.'s trade balance in oil, which is one of the determinants of the exchange rate. Also, in the CUBS model, energy is treated as a factor input. Consequently, a change in the relative price of oil has a bearing on the supply of output in the U.K. economy. In the LBS model, a distinction is drawn between income derived from and expenditure undertaken in connection with North Sea oil. The main effect of these variables on the macroeconomy is transmitted through their influence on government tax revenues. In the CGP model, the North Sea sector is treated as an industry, with a full accounting framework. The extent of the industrial disaggregation in this model permits a detailed investigation of the structural implications of North Sea oil.

The MMB performed simulations in conjunction with four of the U.K. models for the purpose of predicting the macroeconomic consequences of a twenty-five per cent reduction in the dollar price of oil. Analysis was undertaken with each of the CUBS, LBS, NIESR and HMT models. Upon observing the results of the simulations, all of the models predicted that a fall in the price of oil would be beneficial to the output of the U.K. economy. More specifically, according to the CUBS model, fifteen years after the decrease in the price of oil occurred, output would be 2.5 per cent greater than its value in the absence of such a price change.[20] The three quarterly models were used to produce forecasts of a more short-term nature. The maximum number of years ahead for which a forecast was generated was five in the case of the NIESR model and four for both the LBS and HMT models. From the NIESR model, the result was obtained that, following the change in the price of oil, by the end of the simulation period, output would be in the region of one per cent in excess of its base value. For the LBS and HMT models, the corresponding percentages were 1.6 and 0.25, respectively.

For both the exchange rate and the price level, there was seen, across the models, a substantial variation in the predicted effect of the reduction in the price of oil. For example, according to the CUBS model, a fall in the price of oil would stimulate an

[20] This value is referred to as the base value.

appreciation in sterling. In contrast, the NIESR model forecast a depreciation in the U.K.'s currency. More specifically, the CUBS model maintained that, fifteen years after the decrease in the price of oil occurred, in nominal terms, sterling would be 12 per cent above its base value. However, the result that was obtained from the NIESR model was that, by the end of the five-year simulation period, in terms of dollars, the value of the pound would be 20 per cent less than its base value. Also, there was considerable disagreement between the NIESR and CUBS models concerning the response of the general price level to the fall in the price of oil. The CUBS model generated the prediction that, by the end of the simulation period, the price level would be 16 per cent below its base value. The forecast that was produced by the NIESR model, though, was that, five years after the decrease in the price of oil occurred, the price level would be 17 per cent above its base value.

The marked difference in the predictions of the price level by the NIESR and CUBS models is attributable to their contrasting structures. Within the NIESR model, the impact of a change in the price of oil is felt largely on the demand side of the economy. In contrast, the CUBS model gives emphasis to the response of the supply side to this development. However, the two models share in common the feature that the exchange rate represents the principal mechanism via which a shock to the price of oil affects the U.K. economy. To measure the importance of the exchange rate as a channel of influence, for each of the CUBS, LBS, NIESR and HMT models, two sets of simulation results were produced and compared. The macroeconomic consequences of a twenty-five per cent reduction in the dollar price of oil were predicted, first, allowing the exchange rate to be endogenous, then, restricting this variable to be exogenous.

In the case of the NIESR model, when the exchange rate was treated as exogenous, the forecasts of output and the price level deviated to a negligible extent from their respective base values. Concerning the CUBS model, the observation was made that, when the status of the exchange rate was altered from endogenous to exogenous, the impact of the oil price shock was considerably muted. For example, given an exogenous exchange rate, by the end of the simulation period, output was only 0.7 per cent greater than its base value. Similarly, in connection with HMT model, the conversion of the exchange rate from endogenous to exogenous had the effect of dampening the predicted shifts in the values of output and the price level. Out of the four U.K. models, the exchange rate was found to be the least influential in the LBS model. Simulations performed in conjunction with the latter showed that the nominal value of sterling was not seriously affected by the fall in the price of oil.

From the information which is contained within this and the preceding sub-section, it is apparent that the predictions which emanate from a structural macroeconometric model are heavily dependent upon the theory which forms the basis of its construction. Consequently, if a more objective assessment is being sought of the macroeconomic effects of a change in the price of oil then a more data-led approach would be welcomed. Within a significant number of studies which have been devoted to analysing the relationship between the price of oil and macroeconomic performance, James D.

Hamilton has adopted a less formal modelling strategy. In the following section of this chapter, consideration is given to Hamilton's seminal article, which was published in 1983, together with subsequent related empirical work.

2.2 The Contribution and Influence of James D. Hamilton

2.2.1 James D. Hamilton (*Journal of Political Economy*, 1983)

At approximately the same time as the meetings of the EMF working group were taking place, there was being published in the *Journal of Political Economy* what proved to be a highly influential paper by James D. Hamilton (1983). In common with the working group, Hamilton's objective was to investigate the relationship between the price of oil and macroeconomic performance. His study was motivated by the observation that, since the end of World War II, all but one of the recessions occurring in the U.S. had been preceded by a dramatic increase in the price of crude oil. The single exception was the recession in 1960/1961. In contrast to the EMF working group, Hamilton did not use, as a basis for analysis, structural macroeconomic systems. Instead, reliance was placed upon bivariate and multivariate distributed-lag models.

More specifically, Hamilton constructed a version of Sims's (1980b) six-variable macroeconomic system in order to examine the role of the price of oil in the U.S. economy. This system included the variables: real G.N.P.; unemployment; the implicit deflator for non-farm business income; hourly compensation per worker; import prices;

and the money supply (M1). The oil price variable that was involved in this study was the wholesale price index of crude oil. Data on these variables were quarterly, seasonally unadjusted.

Hamilton was aware that, since 1973, oil prices had been determined by a radically different institutional regime.[21] By restricting analysis to a period prior to 1973, then, it was possible to avoid a source of non-stationarity. Another source of non-stationarity was the secular time trend that was common to many macroeconomic series. In general, Hamilton found that it was possible to eliminate the trend in a series by first-differencing the logarithm of the associated variable. In those instances where the correlogram continued to provide evidence of a seasonal unit root, the logarithmic form of the variable was also fourth-differenced.

Hamilton performed bivariate and multivariate Granger-causality tests.[22] The estimation period was either 1949q2-1972q4 or 1950q2-1972q4, according to whether the maximum length of lag on variables was four or eight quarters. Strong evidence was obtained of the price of oil Granger-causing real output and unemployment. In a bivariate model containing four lags on variables, it was possible to reject, at less than the 0.1 per cent level of significance, the null hypothesis that the price of oil does not Granger-cause real G.N.P.. Also, in a bivariate model incorporating eight lags on

[21] Between 1948 and 1972, the Texas Railroad Commission and similar state regulatory agencies constrained production levels in accordance with forecasts of the demand for oil. Sympathies were clearly with the producers such that the regulators made no attempt to accommodate unexpected shifts in supply.
[22] The concept of Granger-causality applies to variables for which the associated time series are stationary. It originates from the article by Granger (1969). In the context of an equation for the current value of Y which includes past values of a second variable, X, as well as lags on Y, itself, X can be pronounced as Granger-causing Y if at least one of the coefficients that are attached to X happens to be non-zero.

variables, the null hypothesis that the price of oil does not Granger-cause unemployment could be rejected at less than the one per cent level of significance. In a bivariate context, Hamilton also found evidence of the price of oil being Granger-caused by import prices.[23] However, further investigation indicated that this significant correlation was not attributable to import prices acting as a proxy for general conditions in the macroeconomy.

Hamilton proceeded to explore the possibility that the significant estimated effect of lagged oil prices on real G.N.P. was spurious and had resulted from the existence of a common influence. Evidence was obtained from three different sources. First, two Granger-causal equations were estimated. One of these equations related output to four lags on both itself and import prices. In the other equation, an attempt was made to explain the variation in the output variable using eight lags on both itself and import prices. Following the application of F tests, for neither of the equations was it possible to reject, at even the forty per cent level of significance, the null hypothesis that import prices do not Granger-cause real G.N.P..

Second, the estimated version of the function that sought to account for the behavior of the price of oil in terms of eight lags on both itself and import prices was used to generate a series of anticipated changes in the price of oil. A series of unanticipated changes was then achieved by subtracting from each actual change the corresponding

[23] Specifically, Hamilton estimated a regression equation which related the price of oil to eight lags on both itself and import prices. Following the application of an F test, he found that it was possible to reject, at less than the 0.5 per cent level of significance, the null hypothesis that lagged import prices have no effect on the price of oil.

expected change in the price of oil. Hamilton, next, constructed an equation which related real G.N.P. to four lags on each of itself, the anticipated change and the unanticipated change in the price of oil. Following estimation and the application of exclusion F tests, strong evidence was obtained of an unanticipated change in the price of oil Granger-causing output.[24] In contrast, the data were not suggestive of a causal role for the anticipated change.[25]

Finally, Hamilton estimated a multivariate model which related real G.N.P. to eight lags on itself, the price of oil and import prices. The outcome of an F test showed that the price of oil contributed significantly to the prediction of output, independent of import prices. The computed value of the F statistic was associated with a probability value of only 0.002. The different forms of evidence compiled by Hamilton thus served to refute the assertion that the significant Granger-causal effect of the price of oil on output had arisen from a common dependence upon past import prices.

Hamilton examined the temporal stability of the causal relationship extending from the price of oil to real G.N.P.. In conjunction with the bivariate equation admitting four lags on variables, a Chow F test was performed. Strong evidence was obtained of a structural change in the relationship from 1949q2-1972q4 to 1973q1-1980q3. The computed value of the F statistic was associated with a probability value of 0.01. Further analysis undertaken by Hamilton showed that, for each of these two periods, it was possible to reject, at a low level of significance, the null hypothesis that the price of oil does not

[24] The probability value corresponding to the computed value of the F statistic was 0.007.
[25] The probability value corresponding to the computed value of the F statistic was 0.36.

Granger-cause output.[26] However, quantitatively, the influence on output of the price of oil appeared to be weaker over the later period.

Following the production of his seminal paper, Hamilton continued to explore the issue of the relationship between the price of oil and macroeconomic performance. Subsequent work by Hamilton, himself, as well as econometric studies which were connected to or motivated by his research, will now be sequentially reviewed.

2.2.2 Further Empirical Analyses by Hamilton and Associated Studies

Gisser and Goodwin (1986) examined the causal relationship between the nominal price of oil and each of the four macroeconomic indicators, real G.N.P., the G.N.P. price deflator, the rate of unemployment, and real investment. The framework that was chosen for analysis also permitted these indicators to be influenced by the policy variables, the money supply and high-employment federal expenditures. The data that were used in this empirical study were quarterly and extended from 1961q1 to 1982q4. Data on all variables were seasonally adjusted, with the exception of the G.N.P. deflator and the price of oil. Data on the price of oil consisted of values of a crude petroleum price index for the last month of the respective quarter.

In this study, each of the variables was contained in the form of a compound annual percentage growth rate, such that stationary time series were involved in the analysis.[27]

[26] For the period, 1949q2-1972q4, the probability value corresponding to the computed value of the F statistic was 0.0005. For the period, 1973q1-1980q3, the corresponding probability value was 0.003.

For each of the macroeconomic indicators, a dynamic equation was constructed. This equation related the indicator to four lags on itself, the price of crude oil and the two policy variables. The four equations were estimated utilising all of the sample data, after which Granger-causality F tests were performed. The results of the F tests showed the price of oil to be statistically informative with respect to the future behaviour of all of the macroeconomic indicators. The probability values that corresponded to the computed values of the F statistics were all less than 0.01.

Gisser and Goodwin proceeded to investigate the notion that the effect of the price of crude oil on the U.S. macroeconomy after the O.P.E.C. embargo was different from that prior to 1973. For all four of the Granger-causal equations, a dummy-variable approach was effectively adopted to allow for a step change at 1973q1 in each of the parameters attached to the oil price variable and the two policy variables. Following estimation of the augmented equations and the application of F tests, there was discovered to be no significant change in the estimated effect of the price of oil on any of the four macroeconomic indicators. The probability values corresponding to the computed values of the F statistics ranged from 0.36 (real G.N.P.) to 0.74 (real investment). As a result of their investigation, Gisser and Goodwin concluded that:

> "…… what has been different about the O.P.E.C.-dominated era is the absolute size of the oil price shocks. But the overall relationship between crude oil prices and the U.S. macroeconomy appears to have been remarkably stable over the past 25 years."
>
> (Gisser and Goodwin (1986, p. 102))

[27] Denoting the original variable by X, the transformation that was applied was $100\{[1 + \ln(X_t/X_{t-1})]^4 - 1\}$.

The study by Mork (1989) was presented as an extension of the earlier empirical analysis undertaken by Hamilton (1983). With respect to the causal effect of the price of oil on real G.N.P., Mork observed the statistically significant results that had been obtained by Hamilton from data extending to 1980. He thus sought to examine whether or not a significant correlation could still be achieved when the sample period was lengthened in order to incorporate the most recent collapse in the oil market. (The article by Mork is the first of several papers which are now to be reviewed which sought to explore the issue of whether or not the macroeconomic consequences of an increase and a decrease in the price of oil are symmetrical.)

The basis for Mork's investigation was the equation for real G.N.P. entering Sims's (1980b) six-variable vector autoregressive (VAR) model. This equation related real G.N.P. to lags on itself, the G.N.P. price deflator, the price deflator for imports, average hourly earnings for production workers in manufacturing, the civilian unemployment rate and the 90-day Treasury bill rate.[28] Mork extended this equation to include lags on the real price of oil. The data used in this study were quarterly and the augmented equation was estimated over the period, 1949q1-1988q2. With the exception of the unemployment rate and the short-term rate of interest, all of the variables entered the equation in the form of an annualised percentage rate of change.[29]

A feature of Mork's study was the construction of a series on the quarterly proportional change in the price of oil, so as to prevent the data from being distorted by the

[28] The Treasury bill rate did not, in fact, feature in Sims's original VAR model. However, Sims (1980a) later employed this as a replacement for the money supply (M1).
[29] Denoting the original variable by X, the transformation that was applied was $400\Delta \ln X$.

imposition of price controls on domestically produced oil during the 1970s. Up to 1971q2, reliance was placed upon the quarterly proportional change in the producer price index (PPI) for crude oil. From 1974q2, Mork utilised the quarterly proportional change in the composite refiner acquisition cost (RAC) for crude oil. For the intervening quarters, 1971q3-1974q1, data were achieved by applying a transformation to the quarterly proportional change in the PPI for crude oil. Specifically, the latter was multiplied by a ratio that was created by dividing the 1970-1974 change in the logarithm of the annual value of the RAC by the corresponding change in the logarithm of the annual value of the PPI.

The equation for real G.N.P. was estimated incorporating four quarterly lags on variables. An exclusion F test was then performed in conjunction with the lags on the oil price variable. The computed value of the F statistic did not permit rejection, at the five per cent level of significance, of the null hypothesis that the real price of oil does not Granger-cause real G.N.P.. The associated probability value was 0.071.

Having selected 1986q1/1986q2 as a break-point, Mork proceeded to perform stability tests.[30] A Chow test was first applied to the equation for real G.N.P., having discarded from the function the lags on the oil-price variable. The value of the F statistic was calculated to be ($F(9, 124) =$) 0.346, giving rise to a probability value of 0.957. The test for structural change was then repeated, having retained in the function the lags on the oil-price variable. On this occasion, the resultant probability value was 0.027. On the

[30] Specifically, in all cases, the form of stability test that was applied was the version of the Chow test appropriate for when the number of sample observations over the second sub-period does not exceed the number of parameters entering the regression function.

basis of the outcomes of the two stability tests, it was inferred that the behaviour of the growth in output is sensitive to conditions in the oil market.

Further statistical analysis that was undertaken by Mork showed that the results that he had obtained from exclusion and stability tests were heavily dependent upon his choice of series to represent the price of crude oil. When reliance was placed upon data on the PPI for crude oil, without correction for the effects of price controls, it became more difficult to reject null hypotheses. Corresponding to the exclusion F test that was performed in conjunction with the lags on the oil price variable, the probability value was 0.140. Also, the application of the test of stability to the equation for real G.N.P. yielded a probability value of 0.188.

Mork proceeded to examine whether or not the temporal instability that had been inferred in connection with the relationship between real G.N.P. and the real price of oil could be accounted for by asymmetrical effects of a rise and a fall in the latter. More specifically, the equation for the growth in real G.N.P. was modified by replacing the original oil price variable by two different measures. One of these variables represented only increases in the real price of oil. Using X to denote the real price of oil, the variable was allocated the value of $400\Delta \ln X$ when the latter was positive, and zero otherwise. The second variable signified only decreases in the real price of oil. Hence, it assumed the value of $400\Delta \ln X$ when the latter was negative, but otherwise was set equal to zero.

Following estimation of the adjusted function over the period, 1949q1-1988q2, Mork performed exclusion F tests. With respect to the null hypothesis that lagged increases in the real price of oil have no effect on the growth in real G.N.P., the value of the F statistic that was produced was associated with a probability value of 0.001. In contrast, concerning the null hypothesis that lagged decreases in the real price of oil have no effect on the growth in real G.N.P., the resultant value of the F statistic was associated with a probability value of 0.152. Mork also conducted an F test of the pair-wise equality of the coefficients that were attached to the variables which separately indicated increases and decreases in the real price of oil. From the computed value of the F statistic, there was derived a probability value of 0.006. Finally, Mork performed a test of stability in conjunction with the amended equation for real G.N.P., having chosen 1986q1/1986q2 as a break-point. The computed value of the F statistic was sufficiently small for it not to be possible to reject, at the thirty per cent level of significance, the null hypothesis of no structural change.

From his empirical analysis, Mork was thus able to infer that the responses of real G.N.P. to an increase and a decrease in the real price of oil are not symmetrical. Moreover, this asymmetry seemed to be capable of accounting for the finding of instability in connection with the relationship between output and the real price of oil. In contrast to Mork, Tatom (1988) obtained evidence of symmetry from conducting an empirical investigation. As will be seen, though, Tatom's specifications drew more heavily upon economic theory. Also, Hamilton (1988) provided reasons for doubting the validity of the results that Tatom had produced.

Tatom adopted both an indirect and a direct approach towards investigating the relationship between the price of energy and output in the U.S.. Initially, reliance was placed upon a simple, reduced-form macroeconomic model. However, later, Tatom sought to estimate a production function for the business sector of the U.S. economy. Both quarterly and annual U.S. data were analysed in this study.

Tatom began his empirical investigation by constructing equations to describe quarterly data on the two components of real G.N.P.. Nominal G.N.P. was specified as being dependent upon the money supply (M1), federal expenditure, a measure of strike activity and the relative price of energy. In order to create a series on the relative price of energy, the PPI for fuels, related products and power was divided by the business sector price deflator. Each of the variables, nominal G.N.P., the money supply and federal expenditure, was contained in the form of an annualised percentage rate of change. In contrast, the relative price of energy entered the equation in the form of a first-difference of an annualised percentage rate of change. All of the explanatory variables were allowed to affect the dependent variable contemporaneously. Additionally, the equation included four quarterly lags on each of the money supply and federal expenditure variables, as well as five lags on the energy price variable.[31]

An equation for the G.N.P. price deflator was specified which incorporated, as explanatory variables, the money stock (M1), dummy variables to represent price controls and decontrols, and the relative price of energy. The variables, the G.N.P. price

[31] The estimates of the coefficients attached to the money supply and federal expenditure variables were constrained to comply with a fourth-degree polynomial.

deflator, the money stock and the relative price of energy, were each contained in the form of an annualised percentage rate of change. Monetary growth was allowed to affect the dependent variable both contemporaneously and with a delay of up to twenty quarters.[32] In contrast, the energy price variable was permitted to exert only a delayed influence on the dependent variable. The lags admitted on the energy price variable extended from one quarter to four quarters.

For both of the relationships describing nominal G.N.P. and the G.N.P. price deflator, the issue of symmetry was explored. Tatom adopted different procedures for the purpose of testing for symmetry. One strategy was to perform a stability test. More specifically, Tatom sought to examine whether or not there had occurred a change in the relationship between the dependent variable and the relative price of energy in moving from a period of mainly increases to a period of predominantly falls in the latter. A second approach consisted of decomposing the annualised percentage change in the relative price of energy into two variables, so as to allow for asymmetrical effects on the dependent variable of an increase and a decrease in the relative price of energy. An F test was then performed of the pair-wise equality of the coefficients that are attached to the variables representing separately upward and downward movements in the relative price of energy.

Tatom estimated the equation for nominal G.N.P. over the period, 1955q1-1986q3, having extended this in two ways. First, a dummy variable was added, as an explanatory

[32] The estimates of the coefficients attached to the money stock variable were constrained to comply with a third-degree polynomial.

variable, in order to prevent, from 1981q2, a systematic overprediction of the growth in G.N.P.. Second, this dummy variable was used to permit shifts in the values of the coefficients that were attached to the energy price variable from 1981q2, when the relative price of energy began falling. Following the application of six t tests and an F test, Tatom found no support for the relationship between nominal G.N.P. and the relative price of energy having altered from 1955q1-1981q1 to 1981q2-1986q3.

To implement the second procedure for testing for symmetry, Tatom, first, made an adjustment to the equation for nominal G.N.P.. Specifically, the annualised percentage change in the relative price of energy was employed in place of its first-difference. However, for consistency with the original specification, six, rather than five, quarterly lags were admitted on this variable. Having applied this modification, Tatom decomposed the energy price variable into two elements, as described above. The newly formed equation for nominal G.N.P. was estimated over the period, 1955q1-1986q3, with, as before, an allowance made for a shift in the intercept term. Tatom then performed an F test of the pair-wise equality of the coefficients attached to the variable representing only increases in the relative price of energy and the variable signifying only decreases. The value of the F statistic that was calculated was observed to be less than the corresponding five per cent critical value. Thus, once again, the evidence did not refute the notion of symmetry.

Tatom estimated the equation for the G.N.P. price deflator over the period, 1955q1-1986q3, having extended this in two ways. First, a dummy variable was added, as an explanatory variable, in order to prevent, from 1982q3, a systematic overprediction of G.N.P. price inflation. Second, a different dummy variable was relied upon in order to accommodate shifts in the values of the coefficients attached to the energy price variable from 1981q2. Following estimation, Tatom performed an F test of the null hypothesis of no change in the effect of the growth in the relative price of energy on output price inflation from 1955q1-1981q1 to 1981q2-1986q3. The value of the F statistic that was calculated was less than one-third of the size of the corresponding five per cent critical value. Thus, strong evidence was obtained in support of the view that the relationship between the G.N.P. price deflator and the relative price of energy is independent of the state of the energy market.

With respect to the equation for the G.N.P. price deflator, in order to implement the second procedure for testing for symmetry, the energy price variable was decomposed into two parts. The modified equation was estimated over the period, 1955q1-1986q3, having allowed for a shift in the value of the intercept term from 1982q3. Tatom proceeded to conduct an F test of the null hypothesis of the pair-wise equality of the coefficients that were attached to the variables indicating separately increases and decreases in the relative price of energy. The value of the F statistic that was calculated was less than sixty per cent of the size of the corresponding five per cent critical value. Hence, adopting this second approach, Tatom, once again, found support for symmetry.

Tatom also investigated the relationship between output and the relative price of energy using the framework of an aggregate production function. The production function that was constructed related the logarithm of business sector output linearly to the following variables:

- the logarithm of business sector hours of labour input;
- the logarithm of the product of the lagged net capital stock and the Federal Reserve capacity utilisation rate;
- the relative price of energy;
- a time trend;
- two variables allowing for shifts in the trend growth in output at 1967 and 1977.

The production function was estimated using annual data over both of the time periods, 1948-1980 and 1948-1985. Following a comparison of the results which were obtained, Tatom was able to conclude that the addition of five years to the sample period, over which the price of energy fell sharply, was of no consequence for the estimates. The function was again estimated over the period, 1948-1985. However, on this occasion, the equation had been modified to allow for a distinction to be made between the influence on output of a change in the relative price of energy over the periods, 1948-1980 and 1981-1985. The subsequent application of a t test by Tatom did not permit rejection, at a conventional level of significance, of the null hypothesis that the two effects are the same.

Tatom also constructed an alternative form of aggregate production function. Specifically, the first-difference of the logarithm of business sector output was related linearly to the first-difference of the logarithm of each of the labour, capital and energy price variables. The equation was estimated using annual data extending from 1948 to both 1985 and 1980. There was only a slight difference observed in the two estimates that were obtained of the energy price coefficient. For the longer of the two periods, the estimate was –0.081, whereas, for the shorter period, the estimate was –0.100.

In connection with the equation for the first-difference of the logarithm of output, the energy price variable was, once again, decomposed into two parts. The amended function was then estimated over the period, 1948-1985. Tatom proceeded to implement an F test of the equality of the coefficients that were attached to the variable representing only increases in the relative price of energy and the variable signifying only decreases. The calculated value of the F statistic was ($F(1, 33) =$) 3.67, which compared with a five per cent critical value that was equal to 4.15. Consequently, once more, the empirical evidence did not refute the notion of symmetry.

In a formal comment on Tatom's study, Hamilton (1988) contested his finding of symmetry, supplying both theoretical and empirical arguments. There are presented below some of the points that were made by Hamilton in relation to the econometric analysis that was undertaken by Tatom. Concern is, first, with the equation for the annualised percentage change in nominal G.N.P.. Attention is then turned to the two different forms of the aggregate production function.

With respect to the equation for the growth in nominal G.N.P., Tatom obtained evidence of stability. However, Hamilton recognised that, in order to achieve such a result, it had been necessary to include in the function a dummy variable which allowed for a shift in the intercept term. Were the latter to have been omitted then, from 1981q2 to 1986q3 (a period over which the relative price of energy was falling), there would have been a tendency to overpredict G.N.P. growth. Tatom attributed this downward shift in the rate of change of money G.N.P. to a decline in the velocity of circulation. Hamilton maintained, though, that the data were incapable of distinguishing between the fall in the relative price of energy and the reduction in the velocity of circulation as responsible for the lower rate of growth of nominal G.N.P.. Furthermore, he considered it to be unlikely that the fall in the relative price of energy did not contribute towards the decrease in velocity. Tatom, himself, had found the estimated relationship between output price inflation and the percentage change in the relative price of energy to be positive. And, there was a widely held belief that the demand for money and the expected rate of price inflation are inversely connected.

Hamilton made a second point with regard to the equation for the growth in nominal G.N.P.. Recall that Tatom obtained the result of no significant change in the estimated relationship between nominal G.N.P. and the relative price of energy from 1955q1-1981q1 to 1981q2-1986q3. Hamilton suggested, though, that an important factor in producing this outcome was the limited number of degrees of freedom that were available for the purpose of estimation over the later time period. Specifically, estimation of an additional seven coefficients was required, utilising only twenty-two sample observations.

Hamilton, next, supplied comments on the empirical analysis that had been performed by Tatom in relation to an aggregate production function. First, he made reference to the equation that was used to describe the logarithm of business sector output. Results appeared to be sensitive to the inclusion of explanatory variables that were designed to allow for shifts in productivity growth. The possibility existed that these movements in productivity growth were exogenous, i.e., unconnected to changes in the energy price regime. However, given endogeneity, it was unclear to Hamilton how Tatom’s finding of stability should be interpreted. The concern about stability was not removed, having observed estimates that were achieved in connection with the equation describing the first-difference of the logarithm of output. Recall that, when the sample period was extended to include data beyond 1981, the estimated negative effect on output growth of a movement in the proportional change in the relative price of energy was seen to diminish.

Finally, in his comment, Hamilton disputed Tatom’s assertion that ample data already existed for the purpose of testing the symmetry hypothesis. The fall in the relative price of energy occurred at approximately the same time as important changes in the velocity of circulation of money and productivity growth, which rendered it difficult to distinguish between the effects of different factors on macroeconomic performance. Also, the backgrounds against which the falls in the relative price of energy took place, in 1981 and 1985, were not the same. The decrease in the relative price of energy in 1981 followed an equally sharp increase in the previous year. In contrast, the reduction in 1985 was preceded by a lengthy period over which the relative price of energy was gradually declining. On the basis of the sectoral-shifts hypothesis, the macroeconomy would receive a greater boost from the earlier, rather than the later, type of decline. An analysis of data over a period extending beyond 1985 would possibly produce evidence that is less favourable towards symmetry.

Within this section, the econometric studies which have so far been reviewed have been concerned with analysing U.S. data. In contrast, Mork *et al*. (1994) sought to investigate whether or not the macroeconomic effects of an increase and a decrease in the real price of oil are symmetrical by acquiring evidence from quarterly, seasonally-adjusted data on an additional six industrialised countries, namely, Canada, France, (West) Germany, Japan, Norway and the U.K..

Mork *et al*. adopted a reduced-form approach towards modelling the relationship between G.D.P. and the price of oil. Initially, an equation was constructed which related the current value of the growth of G.D.P. to its own past, as well as current and past increases and decreases in the real price of oil.[33,34] A preliminary investigation encouraged five quarterly lags to be included on all of the variables.

[33] The series on the increases and the decreases in the price of oil were created in the same way as in the study by Mork (1989).
[34] For convenience, this type of specification will later be referred to as a bivariate equation.

Mork *et al*. also assembled a more extensive model in which the growth of G.D.P. was explained in terms of its own past, current and past values of the two oil price variables, in addition to past values of price inflation,[35] the rate of interest, the rate of unemployment, and the growth rate of the index of industrial production for the member countries of the O.E.C.D.. A further explanatory variable consisted of the value ratio of energy imports to G.D.P.. The rationale that was provided for the inclusion of the latter was that the effect of an oil price shock of a given magnitude would be the greater, the larger is the size of the ratio. Once more, five quarterly lags on each of the variables entered the respective equation.

In connection with the variables which have been mentioned above, which featured in this study, it was considered unnecessary to apply any transformation to the rate of unemployment, the rate of interest or the ratio of energy imports to G.D.P.. In contrast, all of the remaining variables were contained in the form of an annualised percentage growth rate. For each of the countries, the oil price was converted into units of national currency through combining suitably the relevant exchange rate with the world price of Arabian light crude oil. A real price of oil was subsequently achieved by dividing the nominal price of oil by the preferred domestic price index.

For all countries, the estimation period extended from 1967q3 to 1992q4. The bivariate equations for the different countries were estimated as a system, using the Seemingly Unrelated Regressions (SUR) technique. In general, there was observed to be a negative

[35] For all of the countries, with the exception of Norway and the U.K., price inflation was calculated on the basis of the G.D.P. deflator. In contrast, for Norway and the U.K., reliance was placed upon the Consumer Price Index, in recognition of the price of output being heavily influenced by the price of oil.

correlation between the growth of G.D.P. and an increase in the real price of oil. For each of Canada, France, (West) Germany, Japan, the U.K. and the U.S., the sum of the estimated coefficients which were attached to the current and past increases in the real price of oil was less than zero. For Norway, though, the corresponding sum was positive. Moreover, the null hypothesis, which asserted that an increase in the real price of oil has no effect on output growth, could be comfortably rejected, at the five per cent level of significance, for each of Japan, Norway, the U.K. and the U.S..

In general, there appeared to be a positive correlation between the growth of G.D.P. and a decrease in the real price of oil. For all countries, with the exception of the U.K., the sum of the estimated coefficients that were connected to current and past decreases in the real price of oil was greater than zero. Only in the case of Canada was it possible to reject, at the five per cent level of significance, the null hypothesis which stated that a decrease in the real price of oil has no implications for output growth.

Mork *et al*. conducted F tests in order to investigate the pair-wise equality of the coefficients that were attached to the increases and the decreases in the real price of oil. For each of Canada, Japan and the U.S., it was possible to reject the null hypothesis of symmetry at the five per cent level of significance.

The multivariate equations were also estimated using the SUR technique. For all of the countries, with the exception of Norway, the indication was of a negative relationship between an increase in the real price of oil and the growth of G.D.P.. For Norway, the sum of the estimated coefficients which were associated with current and past increases in the real price of oil was positive. In this context, for each of Canada, Japan, Norway, the U.K. and the U.S., it was possible to reject, at the five per cent level of significance, the null hypothesis which maintained than an increase in the real price of oil has no effect on output growth.[36]

Generally, the sum of the estimated coefficients which corresponded to decreases in the real price of oil was positive. However, for both France and the U.K., the aggregate effect was negative. For both Canada and the U.S., it was possible to reject, at the five per cent level of significance, the null hypothesis of no connection between a decrease in the real price of oil and the growth of G.D.P..

Finally, within the multivariate framework, tests were performed in association with the null hypothesis of symmetrical effects of an increase and a decrease in the real price of oil. For Canada, Japan and the U.S., it was possible to dismiss the hypothesis, when using the five per cent level of significance. For the U.K., rejection was also permitted, when adopting the ten per cent level of significance.

Another study which sought to explore the issue of symmetry was conducted by Mory (1993). More specifically, Mory's objective was to compare the effects of an increase and a decrease in the real price of oil on U.S. economic activity.

[36] For France, rejection was possible at the ten per cent level of significance.

Mory's empirical analysis commenced by performing a simple regression of the first-difference of the logarithm of real G.N.P. on a constant and, lagged by one year, the first-difference of the logarithm of the ratio of the price of crude oil to the implicit G.N.P. deflator. Reliance was placed upon annual data and the sample period extended from 1951 to 1990. The estimated relationship between the dependent and explanatory variables was found to be negative and significant at the five per cent level. In particular, the estimate of the elasticity of G.N.P. with respect to the real price of oil was -0.0551.

Mory subsequently decomposed the oil price variable into two elements, adopting the identical approach to Mork (1989). Within the bivariate regression equation, the first-difference of the logarithm of the real price of oil was replaced by two separate measures indicating proportional increases and decreases in the real price of oil. Mory discovered that the estimate of the coefficient which was attached to the variable representing solely increases in the real price of oil was negative and significant at the five per cent level. In contrast, the estimate of the coefficient which was connected to the variable signifying only decreases in the real price of oil was positive and lacking significance at a conventional level.

Mory elected to augment the three-variable regression equation by adding to its right-hand side the growth in each of government purchases and the money supply. Both of these variables were expressed in real terms and were contained in the form of a first-difference of a logarithm. The extended equation was estimated over the period, 1952-1990. Mory's broad findings were unaffected by the expansion of the regression model.

Thus, at the five per cent level, the estimated effect on economic growth of an increase in the real price of oil was significant, while that of a decrease in the real price of oil was insignificant.

Mory proceeded to perform Granger-causality tests. For each of nineteen different macroeconomic variables, three regression equations were constructed. The first equation related the macroeconomic variable to two annual lags on itself, the proportional change in the real price of oil in the current year and in the previous two years. The second (third) equation was identical to the first specification, but employed as a replacement for the annual growth in the real price of oil the variable which indicated solely proportional increases (decreases). All of the equations which were formed were estimated over the interval, 1950-1990. Regarding the equations which included the proportional change in the real price of oil, in fourteen cases, it was possible to reject, at the five per cent level of significance, the null hypothesis of an absence of Granger-causality. For the equations which incorporated, more specifically, increases and decreases in the real price of oil, the comparable figures were fourteen and one, respectively.

Finally, Mory attempted to undertake a disaggregated analysis. Time-series data were collected on personal income and earnings at the industry level (S.I.C. level 2). Following estimation over the period, 1959-1989, it was discovered that the majority of the variables were significantly related to increases in the real price of oil. In contrast, most of these showed no significant association with decreases in the real price of oil.

Some cases were identified, though, where neither type of movement in the real price of oil appeared statistically to be of any consequence.

Within this survey of empirical literature, all of the attempts to model the characteristic of asymmetry have so far been seen to be the same. However, in a reply to an article by Hooker (1996a), Hamilton (1996) recommended what he considered to be a more suitable strategy, which consisted of creating a net oil price increase (NOPI) variable.

An account will be given firstly of the empirical analysis which was undertaken by Hooker (1996a). An objective of the study by Hooker was to test whether or not there had been a change in the relationship between the price of oil and U.S. macroeconomic activity from the pre-O.P.E.C. period to the O.P.E.C. period.[37] As a basis for his investigation, Hooker chose a five-variable VAR model.[38] Permanent fixtures in this model consisted of the price of oil, the three-month Treasury bill rate, the G.D.P. deflator and the import price deflator. Real G.D.P. and the rate of unemployment took turns as the indicator of macroeconomic activity. The data on variables were quarterly and available from 1948q1 to 1994q2.

The price of oil entered a given VAR model alternatively in nominal and real terms. The nominal price of oil was contained in a first-differenced logarithmic form. In contrast, merely a logarithmic transformation was applied to the real price of oil. The series on the change in the logarithm of the nominal price of oil was constructed in accordance

[37] The O.P.E.C. period was defined to be the interval from October 1973 to the present.
[38] Reliance upon a VAR model meant that the summary of Hooker’s study qualified for entry into the final part of this chapter. However, it was considered that greater continuity would be achieved by its inclusion in the current section.

with the method that had been proposed and implemented by Mork (1989). Data on the real price of oil were generated by dividing the PPI for crude oil by the G.D.P. deflator.

Each of real G.D.P., the G.D.P. deflator and import prices entered the VAR models in a first-differenced logarithmic form. In contrast, no transformation was applied to either the three-month Treasury bill rate or the unemployment rate. The VAR models were estimated over the three different sample periods: 1948q1-1973q3; 1973q4-1994q2; and 1948q1-1994q2.[39] For the purpose of estimation over the first sub-period, the models included eight lags on variables. In contrast, when estimation was conducted over the second sub-period and the full data period, six and twelve lags, respectively, were admitted on variables.

Following estimation, Hooker performed Granger-causality tests in order to assess the importance of the lags on the price of oil in explaining the variation in real G.D.P. and unemployment. For the pre-O.P.E.C. period, 1948q1-1973q3, whether the price of oil was measured in nominal or real terms, it was possible to reject, at the five per cent level of significance, the null hypothesis that the price of oil does not Granger-cause real G.D.P.. When the rate of unemployment was used as a replacement for real G.D.P. as the indicator of macroeconomic activity, the same significant result was obtained. In contrast, for the O.P.E.C. period, 1973q4-1994q2, for both the nominal and the real price of oil, it was not possible to reject, at the twenty-five per cent level of significance, the null hypothesis that the price of oil does not Granger-cause real G.D.P.. Even less evidence was found of Granger-causality extending from the price of oil to

[39] These periods do not reflect the observations that were lost in order to accommodate lags on variables.

unemployment. The weakest results, though, corresponded to the full sample period, 1948q1-1994q2. Irrespective of the nature of the oil price variable and whether the VAR model included real G.D.P. or unemployment, it was not possible for the null hypothesis of a lack of Granger-causality to be rejected at the sixty per cent level of significance. Allowing for, from 1973q4, an intercept shift in the equations for real G.D.P. and unemployment, failed to reduce appreciably the probability values.

In conjunction with equations for real G.D.P. and unemployment containing eight lags on variables, Hooker performed three different F tests for structural change, having selected 1973q3/1973q4 as a break-point. These tests consisted of:

(i) a Chow test;

(ii) a test of the null hypothesis that the values of the slope coefficients are unchanged in moving from the first to the second sub-period;

(iii) a Chow test, after having removed the oil price variable from the VAR model.

Irrespective of whether the equation for real G.D.P. featured the nominal or real price of oil, for all three of the tests, the null hypothesis of parameter stability was decisively rejected. The largest probability value that was associated with the computed value of an F statistic was 0.001. In contrast, whether the nominal or real price of oil was included in the equation for unemployment, the evidence obtained from the application of the three tests showed the function to be stable. The minimum probability value that corresponded to the computed value of an F statistic was 0.106. Finally, in the case of both the equation for real G.D.P. and that for unemployment, it was apparent that it was more difficult to reject stability when the VAR model omitted the oil price variable.

Hooker proceeded to examine whether or not a lack of symmetry was capable of explaining the temporal instability that had been observed in the relationship between the price of oil and real output. Consequently, modifications were made to each of the equations for real G.D.P. and unemployment in the VAR models that had been constructed. These alterations included replacing the oil price variable by, in turn: a variable representing only increases in the nominal price of oil; a variable signifying only decreases in the nominal price of oil; both of the previous two variables.

These six newly formed equations were estimated using quarterly data over each of the two sub-periods, 1948q1-1973q3 and 1973q4-1994q2, as well as the full sample period, 1948q1-1994q2. Following estimation, Hooker chose to perform Granger-causality tests. Regarding the first sub-period, it was possible to reject, at the five per cent level of significance, the null hypothesis that oil price increases do not Granger-cause real G.D.P..[40] At the same level of significance, it was also possible to reject the null hypothesis that oil price increases do not Granger-cause unemployment.[41] In contrast, for both the second sub-period and the full sample period, the data indicated an absence of Granger-causality extending from oil price increases to either of the indicators of macroeconomic activity.[42] In the case of oil price decreases, not for any of the three estimation periods or either of the two indicators was it possible to reject, at the twenty-

[40] The probability value corresponding to the computed value of the F statistic was 0.011.
[41] The probability value corresponding to the computed value of the F statistic was 0.034.
[42] With respect to the four F tests that were performed, the probability values ranged from 0.203 to 0.420.

five per cent level of significance, the null hypothesis of a lack of Granger-causality. Indeed, corresponding to the six F tests that were conducted, three of the probability values were in excess of 0.9.

With respect to each of the two equations which accommodated both the variable representing only increases and the variable signifying solely decreases in the nominal price of oil, Hooker applied a Chow test of structural change. The chosen break-point was 1973q3/1973q4. In the case of the equation for real G.D.P., it was possible to reject, at less than the 0.1 per cent level of significance, the null hypothesis of stability. In contrast, concerning the equation for unemployment, the probability value corresponding to the computed value of the F statistic was 0.212.

On the basis of the results that were obtained from the application of Granger-causality and Chow tests, Hooker's overall conclusion was that asymmetry could not account for the observed dramatic diminution over time in the importance of the price of oil towards explaining macroeconomic performance. However, in a retort to Hooker's paper, Hamilton (1996) argued that these results were attributable to the manner in which Hooker had measured oil price increases. Recall that Hooker constructed a variable which represented all of the quarter-to-quarter increases in the nominal price of oil. The design of this variable was such that it imposed the restriction that the macroeconomic response to a correction to an earlier decrease in the price of oil is identical to that to an equal-size movement to a new peak.

The alternative measure that was advocated by Hamilton was a variable that he termed the net oil price increase (NOPI).[43] This variable was formed from a comparison of the price of oil in the current quarter with the maximum value of the price of oil over the past four quarters. More specifically, when the current price exceeded the previous maximum, the variable was allocated a value that was equal to the percentage difference between the two figures. In contrast, when the current price was less than or equal to the previous maximum, the value of the variable was set equal to zero.

Hamilton undertook econometric analysis involving both the original oil price data and the time series on NOPI. Granger-causality tests were performed in conjunction with equations for the growth in real G.D.P.. All of the equations contained lags on real G.D.P. growth, itself, the Treasury bill rate, domestic price inflation, import price inflation and either the proportional change in the nominal price of oil or NOPI.[44] The equations were estimated using data over the full sample period, 1948q1-1994q2, and both of the two sub-periods, 1948q1-1973q3 and 1973q4-1994q2.

Regarding the first sub-period, both of the two oil price variables were found to be statistically informative with respect to the future growth in real G.D.P..[45] In contrast, with respect to the full sample period, there was a lack of evidence to suggest that the lags on the proportional change in the nominal price of oil affect output growth. The probability value that corresponded to the computed value of the F statistic was 0.615.

[43] In a reply to Hamilton's paper, Hooker (1996b) expressed both empirical and theoretical misgivings about this recommended measure.
[44] The number of lags on these variables entering an equation was identical to that chosen by Hooker (1996a).
[45] The probability values corresponding to the computed values of the F statistics were 0.008 (proportional change in the nominal price of oil) and 0.005 (NOPI).

However, in the case of the lags on NOPI, the associated probability value was 0.020. Finally, concerning the second sub-period, for neither of the two oil price variables was it possible to reject, at even the thirty per cent level of significance, the null hypothesis of no Granger-causality.

In conjunction with each of the equations for real G.D.P., Hamilton also conducted a Chow test of structural change from 1948q1-1973q3 to 1973q4-1994q2. With respect to the equation incorporating the proportional change in the nominal price of oil, the probability value that corresponded to the computed value of the F statistic was less than 0.001. In the case of the equation containing NOPI, the probability value was higher. However, the magnitude of this was insufficient to prevent rejection, at the five per cent level of significance, of the null hypothesis of temporal stability.

For each of the two equations describing the growth in real G.D.P., Hamilton proceeded to perform a more specific test. On this occasion, the null hypothesis stated that the coefficients that are attached to the lags on the oil price variable are unchanged from 1948q1-1973q3 to 1973q4-1994q2. Conducting F tests at the five per cent level of significance, contrasting results were obtained for the two oil price measures. In the case of the proportional change in the nominal price of oil, the null hypothesis was comfortably rejected.[46] However, with respect to NOPI, the probability value that was connected to the computed value of the F statistic was 0.102. Consequently, it seemed that the earlier finding of instability was attributable to the occurrence of a change in one

[46] The probability value corresponding to the computed value of the F statistic was 0.016.

or more of the coefficients attached to variables other than the preferred oil price variable.

In a subsequent paper, Hamilton (2003) recommended an alternative oil price measure, which was found empirically to outperform NOPI. In this study, several specifications of the relationship between the growth of G.D.P. and the price of oil were compared. Given that one of these involved an oil price variable that was credited to Lee *et al*. (1995) then it seems appropriate to consider firstly the contribution which was made by the latter.

Lee *et al*. (1995) sought to explore the causal relationship between the real price of oil and macroeconomic activity using quarterly data on the U.S. up to 1992. Their analysis was founded upon approximately the same multiple regression equation for (the annualised percentage growth in) real G.N.P. as had been used by Mork (1989). Recall that this equation related the current value of G.N.P. to past values of itself, the G.N.P. price deflator, the price deflator for imports, a measure of average hourly earnings, the rate of unemployment, the Treasury bill rate, as well as the real price of oil.[47] Additionally, Lee *et al*. followed the same broad approach as Mork towards creating a series on the price of oil.[48]

The equation for real G.N.P. was estimated over the three different data periods: 1949q1-1986q1; 1949q1-1988q2; and 1949q1-1992q3. For the first of these estimation

[47] The equation in this study differed from Mork's in the respect that the behaviour of the import price variable was unaffected by movements in the price of imported oil.
[48] Where possible, Lee *et al*. calculated the average of the corresponding three monthly figures on the price of oil to achieve a quarterly observation, rather than relying upon the figure for a single month.

periods, it was possible to reject, at almost the one per cent level of significance, the null hypothesis that the real price of oil does not Granger-cause real G.N.P.. In contrast, for neither of the other two periods could the same null hypothesis be dismissed at even the forty per cent level of significance. Indeed, the evidence that was accumulated from the application of the three exclusion F tests indicated a deterioration in the predictive power of the real price of oil with the involvement of more recent data in the analysis.

In common with earlier studies, the response by Lee *et al*. to finding evidence of instability was to replace the annualised percentage change in the real price of oil by two variables. These variables were designed to allow for asymmetrical effects on output growth of an increase and a decrease in the real price of oil. The modified equation was estimated over the three different sample periods: 1949q1-1986q1; 1949q1-1988q2; and 1949q1-1992q3. For each of the first two sample periods, the estimated effect on the growth in real G.N.P. of lagged increases in the real price of oil was found to be significant at the five per cent level. For the longest period, significance was obtained at the ten per cent level. In contrast, for none of the three sample periods was the estimated effect on the growth in real G.N.P. of lagged decreases in the real price of oil significant at even the twenty per cent level.

The distinctive feature of the study by Lee *et al*. was the adoption of a generalised autoregressive conditional heteroskedastic (GARCH) modelling procedure for producing normalised forecast errors with respect to the percentage change in the real price of oil.[49]

[49] More specifically, an attempt was made to explain the behaviour of the oil price variable in terms of four quarterly lags on itself. For the purpose of modelling the variance of the forecast error, a GARCH(1,

Out of the single series of normalised forecast errors, two series were created. One of these series was formed by retaining the positive forecast errors but replacing each negative value by zero. The other was achieved by keeping in place the negative forecast errors but substituting each positive value by zero.

The newly created variables, representing separately positive and negative normalised shocks to the real price of oil, were added to both the original and the modified equations for output growth. The extended specifications were then estimated over the three different data periods: 1950q3-1986q1; 1950q3-1988q2; and 1950q3-1992q3. In the context of either model, for all three of the sample periods, it was possible to reject, at less than the 0.1 per cent level of significance, the null hypothesis that lagged positive normalised real oil price shocks have no effect on real G.N.P. growth. In contrast, there was not a single instance in which the data contradicted, at even the twenty per cent level of significance, the notion that lagged negative normalised real oil price shocks exert no influence upon output growth.

In conclusion, the empirical analysis of Lee *et al*. thus, indicated that an oil price innovation has a greater impact on the growth in real G.N.P., the less volatile has been the behaviour of the real price of oil in advance of the disturbance. Additionally, evidence was obtained of asymmetry, with only positive normalised oil price shocks being seen to affect the future growth in output.

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1) process was selected. The GARCH model was estimated using data from 1949q3 to 1992q3. A normalised error was achieved by dividing the residual corresponding to the estimated form of the fourth-order autoregressive model by the square root of the corresponding estimate of the conditional variance.

Within the study by Hamilton (2003), consideration was given to four different specifications for relating the growth of G.D.P. to the price of oil. In particular, Hamilton compared empirically the performances of the following four dynamic models:

- a simple linear relationship between output growth and the proportional change in the price of oil;
- an equation that was influenced by the study of Mork (1989), which permitted only increases in the price of oil to affect the growth of output;
- a specification which included NOPI, as suggested by Hamilton (1996);
- a model that was founded upon the study by Lee *et al*. (1995), which assumed that a given-size increase in the price of oil would have a smaller effect, the larger is the conditional variance. In contrast, under all circumstances, decreases in the price of oil were restricted to be of no consequence for economic activity.

The data which were employed in this study related to the U.S., and extended from 1949q2 to 2001q3.[50] Following estimation and the application of a chi-square test for misspecification, Hamilton was able to reject decisively the null hypothesis of a linear, dynamic relationship between the price of oil and the growth of G.D.P.. The third model, which was based upon the research of Lee *et al*., received the strongest support from the data, while the specification which accommodated NOPI appeared clearly inferior.

[50] The oil price variable was formed by multiplying by 100 the quarterly change in the logarithm of the nominal PPI for crude oil.

Hamilton's response to the results of the chi-square tests was to create a new oil price measure, which was intended as a replacement for NOPI. The variable which was suggested represented the extent to which the current price of oil exceeded its peak value over the previous twelve quarters. For convenience, this will be denoted by NOPI3.[51] Application of a chi-square test revealed the equation which featured NOPI3 to be acceptable (although statistically the specification was inferior to the model which included normalised increases in the price of oil).

In conjunction with each of the aforementioned non-linear models, Hamilton performed tests for structural change with reference to the coefficients which were attached to the lags on the oil price variable. In the case of Mork's equation and the specification incorporating NOPI, the computed value of the relevant chi square statistic was significant at a conventional level. In contrast, in connection with the models which accommodated volatility-adjusted oil price increases and NOPI3, there was no evidence of parameter instability.

Hamilton proceeded to investigate the claim which was made by Hooker (1996) that the observed statistically significant relationship between the growth of G.D.P. and the proportional change in the price of oil was purely attributable to their behaviour prior to 1980. He thus applied OLS estimation to the four non-linear models over different time periods, with the starting date varying from 1948q2 to 1989q4. For each sample period, following estimation, Hamilton performed an F test of the null hypothesis that the

[51] The same as for NOPI, when the current value of the price of oil is less than its earlier maximum then NOPI3 is assigned a value of zero.

coefficients which are attached to the lags on the oil price variable are equal to zero. For both of the models which included NOPI3 and the standardised oil price increases, the computed value of the F statistic was found to be significant as long as the interval incorporated both the 1981 and 1990 oil price shocks. Moreover, for the equation containing NOPI3, there was a suggestion that a significant result could be obtained even when the only surprise event to feature in the data period corresponded to the oil price hike which occurred in 1990.

Hamilton summarised the findings of the fourth section of his paper by pronouncing that:

> "…… neither Mork's measure nor the 1-year net oil increase measure can do an adequate job of capturing a stable nonlinear relation between oil prices and G.D.P. On the other hand, both the 3-year net increase and the Lee *et al*. measure do seem to capture the relation adequately, with the data slightly favoring the latter."
>
> (Hamilton (2003, pp. 385-386))

Having established that the relationship between the price of oil and the growth of G.D.P. was most suitably described by a non-linear equation, in the penultimate section of his paper, Hamilton investigated whether or not the optimal model was allowed a causal interpretation. The approach which he adopted was to examine whether or not there was evidence to support movements in oil price variables as being exogenous.

Hamilton identified five distinct events, occurring between 1956 and 1990, that were responsible for disruptions to the supply of oil, which he maintained could be construed as exogenous. Hamilton proceeded to calculate the percentage shortfall in the production of oil which was associated with each event. The figures which were generated formed the basis for creating a series on a variable, Q, which could be employed as a valid instrument.

The fitted values which were achieved from a regression of the quarterly percentage change in the price of oil on a constant, the current and four lagged values of Q could be viewed as aspects of the movements in the price of oil that were unambiguously attributed to exogenous events. Hamilton observed a similarity between the series of predicted values and the quarterly data on NOPI3. To a lesser extent, this also matched the series on NOPI and the normalised oil price increases.

Hamilton estimated over the full sample period the original linear model for the growth of G.D.P.. However, on this occasion, eight lags on Q and four lags on the dependent variable were employed as instruments. The estimates which were achieved appeared “remarkably” similar to the OLS estimates which were obtained on the basis of pre-1980 data. Also, the estimates were identified as being “quite” similar to those which resulted from estimation of the equation which included NOPI3. Furthermore, a test for structural change was applied, selecting 1972q1 as the break-point. The resultant probability value of 0.15 enabled the inference to be drawn of stability, the implication of which was that the growth of G.D.P. had responded in an equivalent manner to the different exogenous supply shocks.

Hamilton concluded his empirical analysis by evaluating whether or not any of the variables which entered the non-linear specifications contained predictive content which exceeded that which was incorporated within the exogenous component of an oil price change. More specifically, Hamilton constructed a regression equation for the growth in G.D.P. which included four lags on itself and eight lags on Q. This model was supplemented by the separate introduction of four lags on NOPI, NOPI3 and the oil price variables which were attributed to Lee *et al*. and Mork. A test was subsequently performed of the null hypothesis that the coefficients which are attached to the lags on the additional variable are equal to zero. The only significant outcome to emerge related to the normalised oil price increases. The probability value which was associated with the latter was 0.013, which compared with 0.23 for NOPI3, 0.42 for NOPI and 0.40 for Mork's oil price measure.

The final study to be given consideration in this part of the chapter is a relatively recent contribution by Hamilton (2009) which sought to compare the causes and consequences of the oil price rise which occurred in 2007/2008 with those of earlier increases. Hamilton regarded previous oil price hikes as being attributable primarily to disruptions to supply. In contrast, he saw the most recent upward movement as being founded upon a growing demand for oil, in the context of a stagnating world production.

Hamilton adopted different approaches towards establishing the consequences for the U.S. economy of past increases in the price of oil. For example, he utilised the estimated version of a six-variable VAR model that had been constructed by Blanchard and Gali

(2008) in order to generate dynamic forecasts (up to five quarters ahead). Having produced these predictions, Hamilton was able to draw two conclusions: in the absence of an oil price shock, there would have occurred only a very mild recession between 1974q1 and 1975q1; the downturns which were experienced in 1979/1980 and 1990/1991 would not have happened without an increase in the price of oil having taken place.

Hamilton also placed reliance upon estimates which had been achieved in his 2003 study, as a result of performing a regression of the quarterly growth of real G.D.P. on a constant, four lags on itself and four lags on NOPI3 over the interval, 1949q2-2001q3. One-quarter-ahead forecasts were produced on the basis of the actual values of NOPI3 and also through having replaced each of these by zero. After having undertaken suitable comparisons, Hamilton was able to reach the verdict that oil price movements were principally responsible for all four of the pre-2000 recessions.

With a view to understanding the causes of the most recent economic decline, Hamilton, once again, consulted the study by Blanchard and Gali (2008). On this occasion, the respective VAR model was estimated over the sample period, 1948q1-2007q3, having included and excluded the oil price variable. Having contrasted predictions that were generated over the interval, 2007q4–2008q4, Hamilton discovered that the growth of G.D.P. would have been, on average, 0.7 percentage points higher in the absence of an oil price shock. Furthermore, without the occurrence of the rise in the price of oil, the evidence suggested that 2007q4-2008q3 would not have been regarded as the beginning of a recession.

Hamilton obtained further econometric models from his earlier study (Hamilton (2003)), which were estimated over the interval, 1949q2-2001q3. Forecasts of the growth of G.D.P., were produced over the period, 2007q1-2008q4. Considerably greater accuracy was achieved when the specification included NOPI3. In particular, by virtue of incorporating the oil price variable within the equation, the mean square error was reduced by 45 per cent. Furthermore, the unrestricted model was seen to be fully capable of accounting for the economic downturn in 2007/2008.

As a form of conclusion to his analysis, Hamilton pronounced that:

> "…… the evidence to me is persuasive that had there been no oil shock, economists today would be describing the economy in 2007q4-2008q3 as growing slowly but not in recession."[52]
>
> (Hamilton (2009, p. 257))

[52] It should be appreciated that not all economists shared the views that were expressed by Hamilton in this paper. For example, in the discussion which followed its presentation, Kilian argued that none of the oil price increases which had occurred since the early 1970s appeared to be attributable to supply factors. Also, Perry maintained that respect needed to be given to the response by the Federal Reserve to an oil price shock. Furthermore, Romer took issue with the specification of one of Hamilton's regression models, contending that an allowance should have been made for developments in the intensity with which energy was being used in the U.S. economy.

2.3 Vector Autoregressive (VAR) Models

This section makes selective reference to studies of the relationship between the price of oil and macroeconomic performance which have sought to adopt a VAR modelling approach. One of the earliest analyses of this type was conducted by Burbidge and Harrison (1984). A seven-variable VAR model was constructed for the purpose of describing monthly data on each of five countries: Canada; the Federal Republic of Germany; Japan; the U.K.; and the U.S.. More specifically, the variables which entered the VAR system consisted of the relative price of oil,[53] total industrial production in O.E.C.D. countries (other than the country which was under investigation), industrial production in the domestic country, a short-term interest rate, currency and demand deposits, average hourly earnings in manufacturing, and the consumer price index (CPI). All of the variables, with the exception of the rate of interest, were contained in a logarithmic form and subjected to twelfth-differencing, in order to eliminate any seasonal behaviour.

Each of the models was estimated by OLS, using data which extended from May 1962 to June 1982. Burbidge and Harrison found that there was little to be gained by allowing for lags on variables of beyond four months. Additionally, a constant and linear trend term featured on the right-hand side of all of the equations.

[53] The oil price variable was formed by dividing the price of Saudi Arabian (Ras Tanura) crude oil (expressed in dollars per barrel) by a weighted average of the consumer price indices for the five countries which featured in this study.

Following estimation and the application of F tests, Burbidge and Harrison found evidence to suggest that:

- the relative price of oil influences the CPI in all five of the countries;[54]
- the relative price of oil has a bearing upon average earnings in all countries, with the exception of Germany;
- only in the U.K. does a change in the relative price of oil exert a direct effect on industrial production;
- in the U.K. and Germany, the relative price of oil and industrial output are indirectly connected via industrial production in the other O.E.C.D. countries.

The moving average representation of each VAR model was employed to examine the consequences of a shock to the relative price of oil. In particular, Burbidge and Harrison traced the responses over seventy-two months to a one-standard-deviation innovation in the oil price variable. For all countries, the long-run effect on both earnings and the CPI was observed to be positive. In contrast, there was seen to be a negative reaction to this disturbance by industrial production.

With respect to all of the five countries, historical decompositions were undertaken of the behaviour of the CPI and industrial production in the aftermath of the oil price rise in 1973/1974.[55] The results indicated that movements in the price of oil were mostly able to account for general price inflation in Canada and the U.S.. However, with regard to the

[54] The highest probability value was 0.09, for Canada.
[55] Projections were made of the values of these two variables up to June 1982, adopting two different approaches. Baseline projections were achieved through relying upon data up to September 1973. Also, base-plus-oil projections were formed through allowing for the cumulative impact of oil price innovations. Subsequently, these projections were compared with the respective actual values of the variables.

U.K., oil price innovations explained only about a half of the difference between the baseline projection and the actual rate of CPI inflation in August 1975. Finally, knowledge of movements in the relative price of oil appeared to be of little virtue in predicting the rate of consumer price inflation in Japan and Germany in the mid-1970s.

Regarding the historical decomposition of industrial production, for all countries, the baseline projection indicated a significant reduction in the rate of growth of output after 1973. However, with the exception of for Germany, oil price innovations helped to obtain more accurate predictions over a period which extended to late 1975 or early 1976.

Burbidge and Harrison also undertook historical decompositions in the aftermath of the oil price increase in 1979/1980. On this occasion, then, baseline projections were generated, using data up to March 1979. Suitable comparisons revealed that oil price developments made little or no contribution towards the consumer price inflation that was subsequently experienced in the U.K., the U.S., Germany and Canada. In the case of Japan, though, oil price innovations accounted for, to an appreciable extent, the high inflation that occurred in 1979 and early 1980. With regard to the behaviour of industrial production, Japan, once more, constituted an outlier, on the basis that, for all of the other four countries, baseline and base-plus-oil projections differed only slightly.

The results of Burbidge and Harrison suggested that the economic downturn which was endured in the mid-1970s would have taken place even in the absence of the large oil price increases in 1973. Oil price movements merely served to create a deeper recession. Also, baseline projections of the behaviour of the CPI and industrial production in the aftermath of the oil price hike in 1979/1980 were generally discovered to be quite accurate. Hence, the relative price of oil could only be assigned limited responsibility for macroeconomic performance in the early 1980s. These findings encouraged Burbidge and Harrison to conclude that:

> "All in all it is less easy than some might think, it seems, to lay all the blame on external influences, namely O.P.E.C., for the poor economic performance of much of the non-O.P.E.C. world over the past 10 years."
>
> (Burbidge and Harrison (1984, p. 481))

The empirical investigation by Ferderer (1996) shares with the study by Burbidge and Harrison the feature that results were generated from monthly data. More specifically, though, using two different VAR models, Ferderer estimated the effect upon U.S. industrial production of not only the real price of oil but also its volatility.

As a starting point for producing a monthly series on each of the real price of oil and its volatility, Ferderer obtained daily data on spot market bulk prices of refined petroleum products that were shipped from the port of Rotterdam. Specifically, daily data were available on the prices of four refined petroleum products: premium gasoline; jet grade kerosene; gasoil; and heavy fuel oil. Using the relative demands for the petroleum products as weights, for each weekday, a weighted average of the four prices was calculated. A daily series on the real price of oil was then achieved by dividing each of the weighted averages by the consumer price index for the corresponding month. A monthly series on the real price of oil was created by averaging the daily observations. Also, a monthly series on the volatility of the real price of oil was formed by, for each month, calculating the standard deviation of the daily observations.

Ferderer performed analysis in conjunction with two different VAR models. Each of these models included the variables: the real price of oil; the volatility of the real price of oil; (the logarithm of) industrial production; and a measure of the stance of monetary policy. Ferderer's preferred indicator of the nature of monetary policy was the Federal funds rate. However, as an alternative, he used (the logarithm of) non-borrowed reserves. There was a desire to accommodate each of the variables in the models in a manner such that the associated time series was stationary. Following the application of unit root tests, no transformation was considered necessary to the volatility variable. In contrast, it was decided to contain each of the other four variables in the form of a first-difference.

The two VAR models that were constructed included twelve monthly lags on each of the variables. The sample period that was adopted by Ferderer extended from January 1970 to December 1990. Following estimation of both of the models, for all equations, exclusion F tests were performed in conjunction with the twelve lags on each of the variables. In the case of neither model was it possible to reject, at the ten per cent level of significance, the null hypothesis that the real price of oil does not Granger-cause industrial production.[56]

[56] Ferderer attributed this inability to obtain a significant result partly to the existence of a strong correlation between the change in the real price of oil and oil price volatility.

Concerning the lagged effect of the volatility of the real price of oil on industrial production, the result of the F test was found to be sensitive to the VAR model that formed the basis for analysis. In the case of the model including non-borrowed reserves, it was possible to reject, at the one per cent level of significance, the null hypothesis that oil price volatility does not Granger-cause industrial production. In contrast, for the model containing the Federal funds rate, the same null hypothesis could not be rejected at the ten per cent level of significance.

Employing both of the two estimated systems, forecast-error variance decompositions were undertaken at both twelve month and twenty-four month horizons. For both of the models, at both of the horizons, the change in the real price of oil explained a significant proportion of the variance of the growth in industrial production. However, at a twelve-month horizon, the influence of this variable on output growth was weaker than that of either monetary policy or the volatility of the real price of oil.

The estimated models were also used to produce impulse response functions. Each of these functions showed the response of one variable, over a twenty-four month horizon, to a one standard deviation shock to either itself or another variable in the VAR system. For both of the models, an innovation in the real price of oil had a negative influence on the growth in industrial production. However, it took in the region of twelve months for this effect to become significant. The functions that were generated indicated that the response of output growth to a shock to either the change in the real price of oil or oil price volatility was stronger and more significant than its reaction to an unexpected movement in either of the monetary policy variables.

Ferderer proceeded to explore the issue of whether or not the growth in industrial production responds symmetrically to a rise and a fall in the real price of oil, using as a basis the four-variable VAR model which incorporated the Federal funds rate. More specifically, Ferderer adopted the approach of Mork (1989) by substituting the change in the real price of oil by two variables which sought to represent separately increases and decreases. The modified VAR model was estimated using sample data extending from January 1970 to December 1990. Subsequently, Ferderer performed exclusion tests, undertook variance decompositions and generated impulse response functions.

In connection with the equation for the growth in industrial production, for each of the five variables, in turn, an F test was conducted in association with the null hypothesis that each of the coefficients which are attached to the twelve lags on the variable is equal to zero. With respect to the variable representing only increases in the real price of oil, the computed value of the F statistic was 0.89. In the case of the variable signifying only decreases in the real price of oil, the computed value of the F statistic was slightly greater, equal to 0.91. However, neither of these computed values was significant at even the ten per cent level.

In contrast, the variance decompositions that were undertaken showed that both of the two oil price variables had significant responsibility for the growth in industrial production. Moreover, Ferderer found that, at a twenty-four month horizon, the percentage of the variance of output growth that was explained by oil price increases was more than twice the percentage that was accounted for by oil price decreases.

The impulse response functions that were estimated, having allowed for a shock of one standard deviation in the value of each of the two oil price variables, succeeded in providing evidence of asymmetry. In particular, an unanticipated increase in the real price of oil was seen to have a significant, negative effect on the growth in industrial production. In contrast, an unexpected decrease in the real price of oil was observed to stimulate a movement in output growth in predominantly the same direction (albeit, less significant). The resultant functions thus indicated that, whereas an unanticipated increase in the real price of oil would be detrimental to the future growth in industrial production, an unpredicted decrease would fail to deliver any benefit.

Jimenez-Rodriguez and Sanchez (2005) were responsible for an empirical study which has influenced considerably the econometric analysis which is conducted in this thesis. The principal aim of their investigation was to assess the effects of oil price shocks on the growth of real G.D.P. in eight industrialised countries, as well as the Euro Area. Out of the eight countries which featured in this study, Canada, France, Germany, Italy, Japan and the U.S. were classified as oil-importing countries, while both Norway and the U.K. were viewed as exporters of oil.

For each of the countries and the Euro Area, a VAR model was employed to describe the workings of the macroeconomy. The variables which entered the VAR model consisted of real G.D.P., the real effective exchange rate, the real price of oil, the real wage, consumer price inflation, a short-term rate of interest and a long-term rate of interest. More specifically, in all cases, the real price of oil was created by dividing the price of Brent crude oil (in terms of dollars) by the U.S. PPI. Quarterly data were assembled on the variables, extending from 1972 to 2001. The suggestion of the information that was contained in the appendix to this paper was that none of the time series exhibited seasonal variation.

Respecting earlier contributions which had been made towards this field of research, Jimenez-Rodriguez and Sanchez, in fact, constructed four different VAR systems. An initial model constrained the relationships between the variables to be linear. A second specification followed the approach of Mork (1989) by representing separately increases and decreases in the real price of oil. The third model was motivated by the study of Lee *et al*. (1995), and so incorporated volatility-adjusted upward and downward movements in the real price of oil.[57] The design of the final VAR system was inspired by the research of Hamilton (1996), and so included NOPI as the oil price variable.

With the exception of where an attempt was being made to characterise a non-linearity, the manner in which the variables entered the VAR models was governed by the results of different unit root tests. This preliminary analysis was conducted in association with

[57] Indeed, Jimenez-Rodriguez and Sanchez implemented exactly the same procedure as Lee *et al*. in order to generate series of scaled oil price increases (SOPI) and scaled oil price decreases (SOPD).

data on the logarithm of each of real G.D.P., the real price of oil, the real wage and the real effective exchange rate, in addition to the original series on consumer price inflation and the short- and long-term rates of interest. Jimenez-Rodriguez and Sanchez concluded that every variable was integrated of order one, irrespective of the country or region to which it was attached. Consequently, all of these variables were incorporated in the VAR models in the form of a first-difference.

In conjunction with the estimated models, Jimenez-Rodriguez and Sanchez initially undertook Granger-causality tests. One of the tests corresponded to the null hypothesis that, in the equation for real G.D.P., the coefficients which are attached to the lags on the oil price variable are all equal to zero. In the majority of cases, the null hypothesis could not be rejected at the five per cent level of significance. Consequently, the inference was drawn that a change in the real price of oil does not exert a direct effect upon economic activity.

Jimenez-Rodriguez and Sanchez proceeded to explore the issue of block causality. More specifically, likelihood ratio tests were performed in conjunction with the null hypothesis which maintained that, in all of the equations of the respective system but for the equation for the oil price variable, itself, all of the coefficients which are attached to lags on the latter are equal to zero. With reference to the linear model, for every geographical region, with the exception of the U.S., it was possible to reject the null hypothesis at the five per cent level of significance. Concerning the non-linear specifications, for all regions, including the U.S., the estimated effects of past increases in the real price of oil were found to be non-negligible from a statistical perspective. In contrast, for the majority of regions, lagged decreases in the real price of oil appeared to be of no consequence for the performance of the macroeconomy. In this context, though, the U.K. was observed to be an outlier, with both lags on SOPD and Mork's measure being associated with a significant result.

Jimenez-Rodriguez and Sanchez conducted further multivariate tests. For example consideration was given to whether or not the oil price variable was Granger-caused by the other variables which entered the respective system. The null hypothesis of an absence of causality was generally rejected. Indeed, in the case of the U.K., the highest probability value which was obtained was as small as 0.03, corresponding to the linear specification.

Having conducted a variety of exclusion tests, Jimenez-Rodriguez and Sanchez next implemented two different approaches for the purpose of comparing the empirical performances of the different VAR models. The first strategy consisted of observing the confidence bands corresponding to the estimated impulse responses. A study of the relevant diagrams suggested that, for Canada, Germany, the U.S. and the Euro Area, a non-linear specification more accurately characterised the data. In contrast, for the U.K., the linear model seemed more appropriate, while, for the remaining countries, the linear system and the best of the non-linear models generated similarly precise results.

The second approach relied upon comparing values of the Akaike Information Criterion (AIC) and the Schwarz Bayesian Information Criterion (BIC). According to either of the two criteria, for all regions, the specification which included SOPI and SOPD was found to be superior to all of the other three models.

Following the implementation of a Cholesky decomposition, each of the estimated models was employed to generate orthogonalised impulse responses of the six macroeconomic variables to one standard deviation innovation in the real price of oil. With respect to the oil-importing countries, the results indicated a tendency for the estimated effect on the growth of real G.D.P. of a shock to the real price of oil to be negative.[58] However, for Japan, evidence was obtained of a positive relationship, although this outcome was seen not to be robust to an alteration to the order of the VAR model. The non-linear VAR models were associated with larger estimated cumulative responses. In particular, the strongest reactions pertained to the system which accommodated SOPI and SOPD. In general, the growth of real G.D.P. was seen to be more sensitive to an unanticipated increase than an unexpected decrease in the real price of oil. Indeed, the estimated effect of a fall in the real price of oil was found to be insignificant for all of the oil-importing countries, with the exception of Canada.

With reference to the two oil-exporting countries, the estimated cumulative responses of the growth of real G.D.P. to an unexpected increase in the real price of oil were observed not to be even broadly the same. More specifically, the implications of this form of

[58] It was identified that the influence of a change in the real price of oil operated through disturbing the real effective exchange rate.

shock for economic growth were seen to be positive for Norway, yet negative for the U.K.. The contrasting outcomes were attributed to the behaviour of the real effective exchange rate. In particular, for the U.K., the prediction was of a more marked appreciation in the currency. Simultaneously, the positive shock to the real price of oil was shown to stimulate a much larger upward adjustment of the two rates of interest.[59]

The estimated cumulative responses of the growth of real G.D.P. to an unexpected decrease in the real price of oil were also found not to be the same in the two oil-exporting countries. More specifically, a significant result was obtained only for the U.K.. In the context of either of the two VAR models which permitted a separate representation of rises and falls in the real price of oil, an unanticipated decline in the real price of oil was seen to be responsible for enhancing the growth of output in the U.K..

The empirical analysis of Jimenez-Rodriguez and Sanchez concluded by undertaking forecast error variance decompositions in order to establish the relative contributions which were made by different shocks towards the future behaviour of the variables entering the respective VAR model. Their results showed that, for all of the regions, a real oil price innovation assumed considerable responsibility for the subsequent development of a macroeconomic variable. For example, with regard to the growth of real G.D.P., outside of disturbances to itself, shocks to the real price of oil and the short-term rate of interest appeared to be of greatest relevance. Moreover, part of the variation

[59] Furthermore, results indicated that the two countries did not share the same experience in terms of the reaction of the real wage. For the U.K., the estimated cumulative response was negative, while, for Norway, the real wage was discovered to move in the same direction as the real price of oil.

in the short-term rate of interest could be ascribed to an unexpected change in the real price of oil.

In a more recent study, Jimenez-Rodriguez and Sanchez (2009) also undertook empirical analysis in conjunction with VAR models for the purpose of examining the macroeconomic consequences of oil price shocks for several industrialised countries, as well as the Euro Area. On this occasion, consideration was given to five O.E.C.D. countries, namely, France, Germany, Italy, the U.K. and the U.S.. Attention was particularly paid to the implications for output and price inflation of unexpected changes in the price of oil.

As was the case in their earlier paper, Jimenez-Rodriguez and Sanchez constructed four different VAR models. All of these systems included the macroeconomic variables, real G.D.P., the real effective exchange rate, the real wage, consumer price inflation, a short-term rate of interest and a long-term rate of interest, in addition to one or more oil price variables. A linear VAR model was assembled, as well as three non-linear specifications. As before, the latter were influenced by the empirical studies of Mork (1989), Lee *et al*. (1995) and Hamilton (1996).

Results were founded upon quarterly data which extended from 1970q3 to 2003q4. Once more, prior to estimating the VAR models, a preliminary analysis was conducted in order to establish the orders of integration of the contributing variables. Following the application of unit root tests, the series on the growth rates of real G.D.P., the real price of oil, the real effective exchange rate and the real wage were regarded as stationary. However, in order to facilitate economic interpretation, price inflation and the two rates of interest were treated as being integrated of order zero, thus, were admitted to the VAR models without having undergone any transformation.[60]

The preferred specification was decided by a comparison of values of the AIC. In all cases, the optimal system was discovered to be the VAR model which contained the volatility-adjusted measures, SOPI and SOPD. In conjunction with the latter, for all five countries and the Euro Area, forecast error variance decompositions were undertaken with respect to consumer price inflation and the growth of real G.D.P.. After three years, an innovation in the real price of oil was seen to account for between 2.5 and 13.6 per cent of the movement in price inflation. Indeed, the largest figure was associated with the U.K.. With regard to the growth of output, the corresponding range was 2.3-10.8, with the percentage for the U.K. estimated to be 5.8.

Jimenez-Rodriguez and Sanchez also performed historical decompositions with respect to the growth of real G.D.P. and consumer price inflation. From a study of suitable graphs, a conclusion which they reached was that oil price innovations fulfilled a major role in determining the behaviour of output growth and inflation during the periods, 1974q1-1975q1 and 1976q1-1985q4.[61] It was observed for the U.K., though, that, during 1974 and 1979, shocks to the real price of oil were actually assisting output growth. For

[60] Jimenez-Rodriguez and Sanchez maintained that their results were not substantially affected by incorporating these variables in the form of a first-difference.
[61] These were designated periods of high oil prices, on the basis that, over these intervals, the real price of oil exceeded the average that was calculated over all of the sample observations.

all of the regions, real oil price movements were seen to contribute towards the increases in consumer price inflation which were experienced in 1974 and *circa* 1979. Moreover, activity in relation to the real price of oil appeared to be responsible for inflationary pressure which had accumulated within the Euro Area, France, the U.K. and the U.S. during 1999/2000.[62]

To conclude this section, a review is provided of the paper by Jimenez-Rodriguez (2009). This study elected to investigate the issue of a non-linear relationship between the growth of real G.D.P. and the price of crude oil. Consideration was given to the adequacy of specifications which had been adopted in earlier empirical analyses. Also, Jimenez-Rodriguez sought to establish the point in time at which the construction of a non-linear model appeared to be necessary.

The empirical research which was conducted by Jimenez-Rodriguez utilised solely data on the U.S. over an interval which extended from 1947q2 to 2005q2. Initially, a linear bivariate model was constructed, incorporating both real G.D.P. and the price of oil in the form of a first-difference of a logarithm. Estimation was performed over a variety sub-periods. With respect to the full sample period, the inference was drawn that the price of oil does not Granger-cause real G.D.P.. However, when the end date of the estimation period was restricted to preceding 1986q3, predominantly, the evidence supported the existence of Granger-causality.

[62] Additionally, the evidence suggested that developments in the real price of oil played a part in determining U.S. consumer price inflation in 2002/2003.

Jimenez-Rodriguez also assembled a linear VAR model. In addition to the price of oil and real G.D.P., the system included the rate of unemployment, short- and long-run rates of interest, average hourly earnings of production workers, and the consumer price index. With the exception of the rate of unemployment and the two rates of interest, all of the variables entered the model in the form of a first-difference of a logarithm. Four lags were admitted on all of the variables and the sample period extended from 1954q3 to 2005q2. Estimation was undertaken employing different data periods. With reference to the relationship between the price of oil and real G.D.P., in very few instances was it possible to infer Granger-causality from the former to the latter. Following the application of block exogeneity tests, there was no suggestion that the price of oil was Granger-caused by any of the other variables within the system. However, the data indicated that the price of oil Granger-caused at least one of the six macroeconomic variables.

Consideration was next given to non-linear specifications which featured the oil price variables which had been proposed in the studies by Mork (1989), Lee *et al*. (1995) and Hamilton (1996, 2003). It should be mentioned, though, that, in all of the respective models, the restriction was imposed that there are no macroeconomic implications of a decrease in the price of oil.

As before, initially a bivariate analysis was conducted of the relationship between real G.D.P. and the price of oil. Following estimation over the full sample period, 1947q2-2005q2, the evidence suggested that each of the four oil price variables Granger-causes real G.D.P..[63] Estimation was also, once again, performed over different sub-periods. It was observed that Granger-causality could still be inferred as long as, given a fixed starting date of 1947q2, the end date was later than 1963q3. Also, it was found that, in the context of an established end date of 2005q2, for any starting period which came after 1974q1, the data were not supportive of Granger-causality.

A multivariate VAR analysis was also undertaken, involving each of the above four oil price variables. Following estimation over the full sample period, 1954q3-2005q2, in no instance was it possible to conclude that the price of oil Granger-causes real G.D.P.. However, when block exogeneity tests were performed, the evidence indicated that all of the oil price variables, with the exception of NOPI, Granger-caused at least one of the six macroeconomic variables entering the system.

Using each of the linear and four non-linear VAR models, Jimenez-Rodriguez generated one-quarter-ahead predictions over the interval, 1975q2-2005q2. Subsequently, Diebold and Mariano tests were applied to a null hypothesis which maintained equal forecast accuracy. Results showed that each of the non-linear systems produced, on the whole, superior predictions to the linear VAR model. However, not one of the computed values of the test statistic was significant at the ten per cent level.

In association with the equation for real G.D.P., in each of the five VAR models, Jimenez-Rodriguez also proceeded to conduct stability tests. In relation to all of the

[63] For clarification, the four oil price variables consisted of Mork's representation of solely increases in the price of oil, SOPI, NOPI and NOPI3.

coefficients which entered the respective equations, evidence was obtained of structural change. However, with reference to simply the coefficients which were attached to the lags on the oil price variables, the associated null hypotheses could not be rejected.

In order to assess the adequacy of the different specifications, Jimenez-Rodriguez performed non-linearity tests. The framework that was adopted for these tests was an equation for the growth of real G.D.P. which included four lags on both itself and the oil price variable. Following estimation over the period, 1947q2-2005q2, there occurred a rejection of the hypothesis which asserted the validity of a linear equation. In contrast, the data indicated support for each of the non-linear relationships.

Non-linearity tests were also conducted, having estimated the models over various sub-periods. Of interest was the result that the linear specification was unacceptable long before encountering data from the mid-1980s. It also emerged that, with the exception of the equation which featured SOPI, each of the non-linear functions could be inferred as inadequate when the data period ended before 1983q1.

Additionally, Jimenez-Rodriguez contrasted the results of non-linearity tests which were performed over different periods, yet were based upon the same size of sample. In general, the data appeared to favour the specification which incorporated lagged values of SOPI. However, there was evidence to suggest that none of the existing approaches towards characterising the non-linear relationship between output and the price of oil was entirely appropriate.

2.4 Studies Involving an Analysis of U.K. Data

This chapter has sought to show how research has evolved in the area of the relationship between the price of oil and macroeconomic performance. Additionally, the objective has been to indicate the different approaches which have been employed for the purpose of generating empirical results. Thus far, there has been no conscious attempt to give emphasis to findings which have been established for the U.K.. However, respecting the title of this thesis, it seems appropriate to devote a section of this review to a summary of selected studies, not previously mentioned, which have involved an analysis of U.K. data.

There have been few papers which have concentrated solely on the U.K.. However, the article by Holmes and Wang (2003) does enter this category. The aim of the latter was to examine the influence of shocks to the real price of oil on the growth of U.K. G.D.P.. The investigation was strongly motivated by earlier research which had been conducted by Raymond and Rich (1997), who elected to construct a regime-switching model. With reference to the business cycle, an allowance was made for two possible states (expansion and contraction). Both transitional probabilities and average rates of growth were permitted to be a function of the real price of oil.

Holmes and Wang analysed quarterly data which extended from 1960q1 to 2000q1. The oil price was expressed in terms of national currency, using the pound/U.S. dollar exchange rate, and converted into real terms by dividing by the CPI. The data on the real price of oil were suitably combined to form a quarterly time series of net oil price increases, in accordance with the paper by Hamilton (1996).

Maximum Likelihood estimation was applied to four different regime-switching specifications. Following the implementation of nested likelihood ratio tests, the conclusion was reached by Holmes and Wang that oil price developments affect both the deepness and the duration of a business cycle.[64] Their findings were in contrast to those of Raymond and Rich who, for the U.S., had discovered less evidence of transitional probabilities being affected by oil price movements.

Hilde Bjornland has been responsible for two studies which have compared the macroeconomic consequences for two oil exporting nations (Norway and the U.K.) of an energy price shock. The first of these (Bjornland (1998)) was more specifically concerned with the implications for the manufacturing sectors of the two countries. An examination was performed of the effects of demand, supply and oil price shocks. In addition, for the purpose of assessing whether or not the concept of a Dutch disease was valid, consideration was given to the response to an energy boom.

Bjornland's analysis was founded upon a structural VAR model. The variables which entered this system consisted of: manufacturing production; oil and gas extractions; the real price of oil; and output price inflation.[65] Identification was achieved through the

[64] More specifically, an oil price shock was seen to exert a negative effect on the mean growth of G.D.P.. Also, a positive innovation reduced the probability of remaining in the expansion phase of the business cycle.
[65] This variable was subsequently replaced by the rate of unemployment to present an alternative model.

imposition of short- and long-run restrictions that received vindication from economic theory.

Bjornland assembled quarterly data which extended from 1976q1 to 1994q3, and exhibited no seasonal variation. Impulse responses were derived from the estimated versions of the models and showed contrasting results for Norway and the U.K.. More specifically, both an energy boom and a positive oil price shock succeeded in increasing (decreasing) manufacturing output and lowering (raising) the price level in Norway (the U.K.). Thus, the conclusion was permitted that there is stronger evidence of the existence of a Dutch disease for the U.K. than for Norway.

The second study by Bjornland (2000) can be regarded as more extensive than the first, given that it featured an analysis of quarterly data on not only Norway and the U.K. but also Germany and the U.S.. With respect to each of these countries, the aim was to investigate the dynamic effects of aggregate demand, aggregate supply and oil price shocks on G.D.P. and unemployment.

Once again, Bjornland chose to construct a structural VAR model. The latter contained both aggregate demand and production functions, as well as equations which indicated the manner of the determination of prices and wages. The system became identified through the application of short- and long-run restrictions which were founded upon Keynesian theory.

For all countries, the data period terminated in 1994, yet the start date ranged from 1960 to 1969.[66] The price of oil was expressed in units of the national currency and converted into real terms through the use of the implicit G.D.P. deflator, for Germany, the U.K. and the U.S., and the CPI for Norway. On the basis of the estimated impulse responses, the results for Norway were in contrast to those which were obtained for the other three countries. More specifically, for each of Germany, the U.K. and the U.S., a positive shock to the real price of oil served to lower G.D.P. over the following two-to-three years, while ultimately succeeding in raising the level of output in Norway.[67] Compared to Norway, the less favourable impact on economic activity in the U.K. was attributed to different policy reactions. In particular, the U.K. Government had implemented tight fiscal and monetary policies in the 1980s, such that much of the revenue that was derived from higher oil prices was devoted to relieving external debts and funding social security payments.

Cunado and Perez de Gracia (2003) assembled quarterly data on as many as fourteen European countries, including the U.K., for the purpose of exploring the relationship between the price of oil and each of price inflation and industrial production. A feature of their study was the use of four different characterisations of an oil price shock. Denoting the real price of oil in the current quarter by oil_t, the respective definitions are supplied below:

[66] The respective start years were 1960 for the U.S., 1966 for the U.K., 1967 for Norway, and 1969 for Germany.
[67] For all four of the countries, only a weak relationship was established between the real price of oil and the rate of unemployment.

- inter-annual changes, $\Delta oil_t = log.(oil_t) - log.(oil_{t-4})$;
- oil price increases, $\Delta oil^+_t = max.(0, \Delta oil_t)$;
- net oil price increases,

  $NOPI_t = max.(0, log.(oil_t) - log.(max.(oil_{t-4}, oil_{t-8}, oil_{t-12}, oil_{t-16})))$;
- scaled oil prices,

  $SOPI_t = \Delta oil_t / s.d.(\Delta oil_t)$, where the denominator is the square root of the conditional variance of Δoil_t, founded upon a GARCH(1, 1) process.

Cunado and Perez de Gracia formed two different time series on the real price of oil. One of these was achieved by dividing the world dollar price of oil by the producer price of all commodities. The second was created by dividing the world price of oil, converted into units of national currency, by a consumer price indicator for the respective country. The chosen output measure consisted of an industrial production index,[68] while the inflation data reflected percentage changes in consumer prices. The quarterly time series exhibited no seasonal variation and, for the majority of the countries, extended from 1960 to 1999.[69]

Cunado and Perez de Gracia performed a cointegration analysis in order to assess whether or not stable long-run relationships existed between the variables. Also, dynamic models of short-run behaviour were estimated which permitted the inference to

[68] With the exception of Greece, for which the output variable was the more specific index of manufacturing production.
[69] For both Portugal and Denmark, the availability of data was more limited.

be drawn for the U.K. that the real price of oil Granger-causes industrial production.[70] However, only when the price of oil was expressed in terms of units of national currency was it possible to reject at a conventional level of significance the null hypothesis of an absence of Granger-causality from the real price of oil to consumer price inflation.[71] Subsequent analysis was undertaken with the objective of testing for asymmetrical effects of increases and decreases in the real price of oil on the growth of industrial production. Incorporating lags on each of Δoil^{+} and NOPI in relevant specifications, the evidence was seen to be mixed for the U.K..[72]

A multi-country empirical investigation was also conducted by Bredin *et al*. (2010). More specifically, data were analysed on each of the G-7 countries for the purpose of investigating the relationship between industrial production and uncertainty surrounding the price of oil. In particular, there was a desire to establish whether or not the observed unequal effects of a rise and fall in the price of oil on economic activity were attributable to their implications for uncertainty

In this study, results were founded upon the estimation of a structural VAR model which had been adapted to incorporate the feature of multivariate GARCH in mean. The variables which entered the system consisted of: the domestic consumer price index; the domestic index of industrial production; the cost of imported oil, expressed in terms of national currency; a short-term rate of interest; and a measure of oil price volatility, as

[70] The only insignificant result corresponded to the use of SOPI as the oil price variable. (See Table 7, p.147).
[71] See Table 8, p. 148.
[72] See Table 9, p.149.

represented by the conditional standard deviation of the price of oil. The variables were contained in a form such that they corresponded to stationary time series.[73] Full Information Maximum Likelihood was employed as the estimation procedure.

For each of the seven countries, monthly data on the variables were available from 1974 to 2007. Following estimation, attention was paid to the influence of oil price uncertainty upon industrial production. The respective coefficient estimate was negative for all countries and statistically significant at the five per cent level for Canada, France, the U.K. and the U.S..[74] Moreover, these findings seemed to be insensitive to modifications which were made to the original model.

In connection with the aforementioned four countries, impulse responses were generated. The reaction of industrial production to a positive oil price shock was observed to be uniformly negative. Also, an unexpected decrease in the price of oil motivated a significant fall in output over the following one-to-three months for Canada, the U.K. and the U.S.. For France, though, while economic activity was continually depressed, the estimated effect was not significant.

In contrast to Bredin *et al.*, Yoshizaki (2011) was concerned with only a sub-group of the G-7 countries. The essential aim of this study was to assess empirically the effects of oil price shocks on output and prices in each of Japan, the U.K. and the U.S..

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[73] The baseline model included Δlog.(CPI). However, for Canada, Italy, Japan and the U.K., this was subsequently replaced by ΔCPI.
[74] See Table 4, p.27, Bredin *et al*. (2010).

Once more, a structural VAR model constituted the preferred framework for analysis. In particular, Yoshizaki adopted the simultaneous equations system that had been employed by Kilian (2009), which permitted distinctions to be made between shocks relating to the supply of oil, aggregate demand, and oil-specific (precautionary) demand. The variables which entered the model consisted of: world crude oil production; world industrial production; and the spot price of crude oil, deflated by the U.S. CPI.

Monthly data were collected which ranged from 1973m1 to 2010m12.[75] Having estimated the structural VAR model, it was possible to obtain time series that corresponded to the three different shocks. Dynamic regression equations were then constructed to assess, for each of the three countries, the macroeconomic implications of each of the three disturbances.

More specifically, regressions were performed in conjunction with quarterly data, involving real G.D.P. and the CPI as dependent variables. From the results which were achieved, it was apparent that a macroeconomic variable was not affected in the same way by the different shocks. An inspection of the graphs of the cumulative responses revealed that, for the U.K., the aggregate demand innovation exerted the most significant influence upon G.D.P., while a disturbance to oil-market specific demand had the strongest effect on consumer prices.[76] Overall, the findings for the three countries were considered to be similar. Perhaps the most interesting discovery which stemmed from

[75] Data series were chosen which did not exhibit seasonal variation.

[76] In particular, a positive aggregate demand shock was responsible for a temporary increase in output, while a positive oil-specific demand innovation stimulated a sustained upward movement in the general price level.

this analysis was that Japan's G.D.P. benefited from a positive oil-specific demand shock, which Yoshizaki suggested was possibly attributable to the shift towards more oil-efficient goods in production.

2.5 Summary

The objective of this chapter has been to provide a review of some of the applied studies which have been devoted to the subject of the relationship between the price of oil and macroeconomic performance. Through conducting this survey, it has been possible to develop an awareness of the different approaches which have been relied upon for undertaking empirical analysis. At the same time, it has permitted a view to be formed concerning where the balance of evidence lies in respect of the influence of oil price movements on the behaviour of a macroeconomy. In particular, the penultimate section has highlighted results which have been obtained from an evaluation of U.K. data.

It was seen towards the start of this chapter that it is possible to derive conclusions from having estimated and performed simulations in conjunction with a structural macroeconometric model. In this context, though, there is the potential for economic theory to have a strong bearing upon the findings, through contributing towards the design of the system and suggesting restrictions to be imposed upon values of parameters.

James D. Hamilton has undertaken a more data-led approach towards establishing the relationship between the price of oil and macroeconomic performance, which has consisted of estimating dynamic regression models and proceeding to conduct statistical inference. The paper that was published in the 1983 edition of the *Journal of Political Economy* served to stimulate several similar analyses. A significant contribution was provided by Knut Mork (1989), who sought to investigate whether the macroeconomic effects of an increase and a decrease in the price of oil are symmetrical.

Following Mork's study, different recommendations were made concerning how to characterise asymmetric responses. In particular, Lee *et al*. (1995) proposed deflating unanticipated increases and decreases in the price of oil using an estimate of the conditional standard deviation. By virtue of scaling unexpected movements in the price of oil in this way, a given-size change in the price of oil was allowed to have a greater impact during a period of stability, compared to when oil price behaviour was erratic.

In contrast, Hamilton (1996, 2003) advocated the construction of a net oil price measure which contrasted the price of oil in the current quarter with its maximum value over the previous four or twelve quarters. This variable was designed in such a way that an increase in the price of oil would only be influential when it involved a movement to a new peak. A decrease in the price of oil and a rise which was simply a reversal of an earlier fall were constrained to having no effect.

Over the past thirty years or so, a popular approach towards investigating the connection between the price of oil and macroeconomic performance has been to construct a VAR model. Compared to a structural macroeconometric model, the latter offers the data greater scope to determine relationships between the respective variables. In conjunction with the estimated form of a VAR model, researchers have typically proceeded to conduct Granger-causality tests, generate impulse responses, and undertake forecast-error variance and historical decompositions. It should be appreciated, though, that empirical analysis which uses the framework of a VAR system is not a solely objective exercise. Decisions have to be taken concerning the variables to enter the VAR model, the order of the latter, and the means by which the identification problem is going to be solved.

Section 2.4 represented an attempt to bring together some empirical studies that had not been referred to earlier and which had attempted to generate some findings for the U.K.. From a consideration of the results which have been reported on the U.K. in this chapter, there is evidence to suggest that, in spite of the two countries both being oil-exporting nations, the U.K. has responded very differently from Norway to an oil price shock. Mork *et al*. (1994), Jimenez-Rodriguez and Sanchez (2005), and Bjornland (1998, 2000) have all shown that an unexpected increase in the price of oil is beneficial for output growth in Norway, yet has a detrimental effect in the U.K.. However, while Jimenez-Rodriguez and Sanchez attributed the adverse reaction in the U.K. to an appreciation in sterling and upward movements in the rate of interest, Bjornland maintained that contractionary macroeconomic policies offered an explanation.

Nevertheless, on the basis of the literature review that has been conducted in this chapter, there must be a reluctance to reach any definitive verdict concerning the relationship between the price of oil and U.K. macroeconomic performance. The conclusions from the different investigations have the potential to vary on account of differences in sample periods, econometric approach, definitions of variables, and the role that is permitted to economic theory. Thus, the manner in which this thesis proceeds is to make an informed judgement about the most suitable methodology to apply and to trust the validity of the empirical results which follow from its implementation.

CHAPTER THREE

METHODOLOGY: CHOICE OF DATA AND FRAMEWORK FOR ANALYSIS

3.1 Framework for Analysis

The principal aim of this thesis is to undertake an econometric investigation of the relationship between the price of oil and U.K. macroeconomic performance. A fundamental decision to be taken, then, at the outset of the empirical element is the framework to adopt for analysis. The earlier review of the applied econometric literature has indicated the possibility of using either or both of two broad approaches. One strategy consists of conducting a single-equation analysis in which specified econometric equations are treated as separate entities. However, the superior policy would seem to involve assembling a system of macroeconometric equations, thereby accounting for potential inter-relationships which exist between the variables that enter the model.

A choice is available in terms of the type of macroeconometric system that can be constructed. More specifically, two contrasting designs are a structural macroeconometric model and a vector autoregressive (VAR) model. Towards the end of the 1970s, large-scale structural macroeconometric models were popularly used as a basis for forecasting, policy evaluation and the testing of hypotheses concerning relationships between macroeconomic variables. A structural macroeconometric model is a system of equations, the specifications of which are partly influenced by economic theory. Consequently, within a structural model, economic theory contributes towards the decision of whether a variable is classified as endogenous or exogenous. Thus, a distinguishing feature of a structural model is that feedback is somewhat limited between the constituent variables. If the restrictions which are imposed in order to produce the structural model are valid then the benefit will be relatively reliable estimates of the parameters of the stochastic equations. However, should feedback be falsely denied then there will be a cost incurred of biased parameter estimates and erroneous statistical inferences.

In a seminal paper, Sims (1980b) launched a scathing attack on the standard approach towards econometric investigation in relation to Macroeconomics. He expressed a concern with the use of large-scale structural macroeconometric models, which was the attempt to achieve identification of the stochastic equations of the system through the application of inappropriate restrictions. For example, he maintained that, on occasions, variables have been treated as exogenous purely because the model-builder has been unwilling to extend the system in a certain direction. Also, policy variables have conveniently been regarded as exogenous, even when including a substantial endogenous element.

In the context of a dynamic model, Sims also made reference to the unsuitable categorisation of lagged dependent variables with strictly exogenous variables. He argued that a common classification is only acceptable when, *a priori*, the investigator has knowledge of the maximum length of lag and the shape of the distributed-lag function.

The objections which were expressed by Sims to placing dependence upon a structural macroeconometric model encouraged him, in section 2 of his paper, to propose a general strategy for estimating profligately parameterised macroeconomic systems. More specifically, Sims advocated the estimation of large-scale macroeconomic models as a system of unrestricted reduced-form equations in which all of the variables are treated as endogenous. The form of model in which the current value of every variable is linearly related to past values of itself and all of the other variables entering the system is known as a vector autoregressive (VAR) model.[77]

Thus, Sims was responsible for recommending a largely atheoretical approach towards empirical economic analysis. Compared to a structural macroeconometric model, the distinguishing feature of a VAR model is that allowance is made for feedback to exist between all of the variables which enter the system. In the most basic form of a VAR model, all of the variables are treated symmetrically. Hence, there is no need to classify variables as being endogenous or exogenous.

When undertaking an empirical analysis of the relationships between macroeconomic variables, though, it is impossible to deny economic theory completely an input. Thus, in adopting a VAR approach towards modelling, economic theory is allocated the task of deciding upon the variables which enter the system. In contrast, it is the role of the data to determine the maximum length of lag on a variable. On the contrary to a structural model, there is no attempt to reduce the size of a VAR model by discarding irrelevant parameters. Almost inevitably, then, a VAR model will be

[77] More specifically, this represents the standard form of VAR model.

overspecified and it is difficult to lend interpretations to the estimates of the coefficients. However, as will be discussed in greater detail later in this chapter, it is easier to recognise relationships between the participating variables by considering the estimated form of the moving average representation of a VAR model.

3.2 Choice of Variables

The prior discussion indicates a preference for relying upon a VAR system, rather than a structural macroeconomic model, for the purpose of conducting econometric analysis. Having favoured a VAR construction, a key decision concerns the economic variables to be included within this framework.

As has been mentioned in the literature review, a seminal empirical contribution towards the study of the relationship between the price of oil and macroeconomic performance is the article by Hamilton (1983). Hamilton extended a version of the six-variable macroeconomic system which was assembled by Sims (1980b) by adding to this the price of oil. Hence, the variables which initially entered Hamilton's analysis consisted of: two output variables (real G.N.P. and unemployment); three price variables (the implicit price deflator for non-farm business income, hourly compensation per worker, and the price of imports); a variable representing the financial sector (M1); and the price of oil

There are two reasons, though, for rejecting Hamilton's set of variables. First, the model was constructed with the objective of investigating the relationship between the price of oil and the macroeconomy of 'the U.S.'. It must be recognised that the

U.K. possesses a more open economy than the U.S.. Hence, it may be considered to be more essential to incorporate within a model of the economic system of the U.K. variables which determine the country's import and export performance. An obvious candidate for inclusion is consequently the exchange rate. The presence of an exchange rate variable in a model of the U.K. macroeconomy would seem to be especially relevant, respecting the possible applicability to this country of the Dutch disease, to which reference was made in Chapter 1.

A second argument against following the approach of Hamilton, in terms of the choice of variables, concerns the data periods that were employed in his study. Initially estimation was performed using a sample period which extended from either 1949q2 or 1950q2 to 1972q4. Later, the relationship between the price of oil and U.S. output was investigated over the interval, 1973q1–1980q3. There is a desire in this thesis to operate in conjunction with data from 1972 to beyond the year 2000, deliberately limiting the period of analysis to when the U.K. has experienced a floating exchange rate.[78] Thus, even if the augmented version of Sims' model were to provide the foundation for the econometric results that are produced in this thesis, the substantial contrast between the data periods that were chosen by Hamilton and the period that is preferred in the current study would render any comparison with Hamilton's conclusions of little relevance. It would seem to be more beneficial to base the empirical investigation upon a VAR model which features in a more recent publication and which has been estimated over an interval which is not too far removed from that which is to be employed in this thesis.

[78] The decision not to combine data from fixed and floating exchange rate eras stems from the aim to reduce the potential for the relationships in the VAR model to be subject to structural change.

A VAR model which satisfies these requirements is to be found within the article by Jimenez-Rodriguez and Sanchez (2005). Indeed, within this study, Jimenez-Rodriguez and Sanchez performed analysis in conjunction with four different VAR systems. One of these constrained the macroeconomic effects of an increase and a decrease in the price of oil to be symmetrical, whereas the other three represented non-linear specifications. The fundamental variables which entered each of the four frameworks consisted of: real G.D.P.; the real effective exchange rate; the real price of oil; the real wage; price inflation; a short-term rate of interest; and a long-term rate of interest. As was mentioned in Chapter Two, in the literature review, each of the systems was estimated using quarterly data from 1972q3 to 2001q4 on each of eight O.E.C.D. countries, as well as the Euro Area. The decision is taken in this thesis to adopt two of the models which were constructed by Jimenez-Rodriguez and Sanchez, namely, the linear system and what was found to be the empirically superior non-linear specification, which accommodated scaled unanticipated increases and decreases in the real price of oil.

3.3 Frequency of the Data

Partly for ease of comparison, then, the seven-variable VAR model which is outlined immediately above provides the foundation for the results which are to be produced within this thesis. Having decided upon a collection of variables to enter the VAR model, a choice exists concerning the frequency of the time-series data to collect on each of these.

The most frequent basis on which data are available on all of the aforementioned variables is quarterly. Consequently, there is the possibility of performing an analysis in conjunction with either quarterly or annual data. Convention guides the researcher towards a dependence upon the data which are of the higher frequency for the reason that this will give rise to a larger size of sample and number of degrees of freedom. *Ceteris paribus*, the greater are the number of degrees of freedom, the more reliable will be the associated parameter estimates. However, before proceeding resolutely towards a consideration of quarterly data, respect should be paid to a literature within Econometrics which has debated whether the frequency is of limited importance, compared to the span of the data. The summary which is provided below focuses upon the properties of tests for cointegration and a unit root.

Shiller and Perron (1985) contrasted powers of tests of the random walk hypothesis, having imposed a fixed span but having allowed the frequency of the observations to vary. The conclusion which was reached was that power is more heavily influenced by the span than the sample size. In a subsequent paper, this finding was supported by Perron (1991), having also conducted Monte Carlo experiments.

The simulations which were undertaken by Shiller and Perron (1985) and Perron (1991) were targeted at data which were sampled at discrete points (i.e., stock data). In contrast, Ng (1995) sought to investigate the influence of the span and the number of sample observations on the properties of a unit root test that is applied to flow data (i.e., temporally aggregated data). Ng performed one thousand replications of an experiment in an attempt to acquire information on the statistical properties of five unit root tests which made allowance for autocorrelation. A study of Table 1 (p. 240) permitted the conclusion that, in general, the power of a unit root test is lower when applied to flow data than stock data. Also, for three of the tests, it appeared that the consequence of increasing the number of sample observations, while constraining the span to be fixed, is an improvement in power, but at a diminishing rate.

The paper by Pierse and Snell (1995) was also concerned with the results of unit root tests which were founded upon flow data. The principal objective of the study was to examine the effect of temporal aggregation on the power of a unit root test. There were three distinct elements to this article: a theoretical analysis; Monte Carlo simulations; and a macroeconomic example.

In section 2, according to Proposition 1 (p. 336), any statistic which is constructed for the purpose of testing the null hypothesis of a unit root against a one-sided local alternative hypothesis has a limiting distribution which is independent of the frequency of sampling. The conditions upon which this proposition is based were considered to be weak, such that they were satisfied by popularly-applied unit root tests.

The essential result to emerge from section 3 of the paper was that, in order to maintain constant power in the presence of temporal aggregation, an increase in the span of the data is required. In most cases, though, the necessary extension of the span was found to be very small in comparison to the order of the aggregation.

In the concluding section of the paper, reference was made to a study by Molana (1991) of the relationship between non-durable consumption and wealth for the U.K..

Having analysed quarterly data from 1966q4 to 1981q4, Molana was unable to reject a null hypothesis which stated an absence of cointegration. Pierse and Snell were able to demonstrate that a reliance upon annual data over a slightly longer time span was capable of reversing the inference that was drawn.[79]

Haug (2002) conducted Monte Carlo simulations with the objective of quantifying the trade-off between span and data frequency when testing for cointegration. Consideration was given to the properties of several different univariate and multivariate tests. Initially, Haug collected monthly data on a short- and long-term rate of interest for Canada, extending from 1960:01 to 1998:12. He then produced corresponding quarterly and annual time series as a result of calculating suitable averages. When investigating whether or not the two rates of interest cointegrate, Haug observed that the absolute values of the test statistics declined markedly with temporal aggregation. Hence, it appeared that any gain in power which was achieved by the use of lower-frequency data was being more than offset by the loss which was the consequence of a smaller sample size.

Haug then proceeded to create 564 artificial time-series observations on two variables, x and y.[80] An attempt was made to produce time series which incorporated features which were often encountered in Economics, e.g., autoregressive conditional heteroskedasticity, outliers and a leptokurtic distribution. In conjunction with each of the data-generating processes, five thousand replications were undertaken. Haug observed that the power of all of the tests for cointegration fell with temporal

[79] To be more specific, in the case of an Engle-Granger, augmented Dickey-Fuller test, the sample extended from 1957 to 1981.
[80] The choice of 564 observations was intended to correspond to the quantity of monthly data on economic variables which were available after the end of World War II.

aggregation. Moreover, power was most notably reduced when progressing to the use of annual data. However, there was found to be a benefit from analysing the latter, if the span of the annual time series was longer than that of the monthly time series. More specifically, in almost all cases, the power of the cointegration test was seen to be greater for the annual data, having constrained the number of monthly observations to be 564, while permitting the number of annual values to exceed 78.

Chambers has recently had published two papers (2004, 2008) which focus upon the issue of the importance of data frequency, compared to span. Admittedly, though, the purpose of the later article was to correct an aspect of the earlier one. Chambers (2004) was concerned with the properties of two tests for a unit root which were performed in conjunction with flow data. The paper contained theoretical analysis, as well as a report on the results which were obtained from Monte Carlo simulations. Chambers was able to conclude from his study that, in contrast to in the presence of stock data, a unit root test is consistent when applied to flow data, even when the span of the data is not increasing.[81] However, this finding was sensitive to the exclusion of an intercept term from the respective regression equation. Given the inclusion of an intercept term, it was necessary to extend the span of the data in order to achieve consistency.

In a *corrigendum* (2008), Chambers confessed to an error in relation to Theorem 1 in his earlier paper, which necessitated a modification to the analysis concerning a regression equation without an intercept term. The consequence of the revision was that only when the span of the data is increased does a unit root test have the property

[81] In this context, by consistent is meant that, as the sample size increases towards infinity, the power of the test approaches one.

of consistency. Thus, it is apparent that Chamber's conclusion, with respect to flow data, was qualitatively the same as that reached by Perron (1991) for stock data.

The above review indicates that there may be some merit in performing analysis with annual data, rather than quarterly data, if the former are available over a longer time period. However, a decision which has already been taken in this thesis, in an attempt to lessen the risk of relationships being subject to structural change, is to rely upon time-series data which follow the end of the Bretton-Woods era. If the choice, then, is between using quarterly or annual data over a common interval, from the early 1970s to beyond 2000, the results which have emanated from the above studies (e.g., Ng (1995), Haug (2002)) suggest that a benefit may be derived from operating in conjunction with the higher-frequency data.

3.4 Seasonal Adjustment of the Data

A key consideration in any study which seeks to analyse time-series data which are recorded at more frequent intervals than once a year is whether to operate in conjunction with seasonally-adjusted or unadjusted data. Arguments can be presented in favour of both types of data. At the outset of this section, the pronouncement will be made that the preference is for utilising seasonally-adjusted data. Most of the empirical investigations which have been undertaken in time-series Econometrics appear to have involved a reliance upon seasonally-adjusted data.

Recourse to the same type of data will thus facilitate a comparison of results.[82] Additional reasons include:

- a desire to focus upon that part of a variable which is within the control of a policy-maker;
- seasonally-adjusted data tend to be associated with simpler economic relationships;[83]
- an expectation of a greater number of degrees of freedom, on account of shorter lag lengths being acceptable;
- the occurrence of fewer diagnostic problems, e.g., higher than first-order autocorrelation in the error terms of an equation;
- the removal of an opportunity for achieving spurious relationships;
- an elimination of the need to characterise seasonal behaviour within the econometric model.

However, having elected to undertake an analysis of adjusted data, it is essential to recognise the biases and distortions which may result. Indeed, a substantial literature has emerged which has sought to indicate, through performing mathematical derivations and simulation exercises, the econometric consequences of working in conjunction with seasonally-adjusted data. Hence, there is provided, immediately below, a reasonably compact review of some of the studies which have sought to explore the econometric costs of removing seasonality from time-series data.

[82] In particular, it should be recognised that the findings of Jimenez-Rodriguez and Sanchez (2005) were founded upon seasonally-adjusted data.
[83] See the examples which are contained in footnote 1 on p. 18 of the paper by Wallis (1974).

A study to which reference has already been made is the seminal contribution by Wallis (1974). Wallis's objective was to examine the effects on the relationship between two time series of applying an official seasonal-adjustment procedure.[84] The conclusions which were reached were founded upon both theoretical analysis (Section 2) and the results which were obtained from simulation experiments (Section 3).

The theoretical findings relied upon a linear approximation to the official method of seasonal adjustment. Wallis demonstrated that if the same filter is used in conjunction with both the series on the dependent variable and the series on the explanatory variable then the relationship between them will be undisturbed. Merely, the statistical properties of the error term will be affected. In contrast, though, when only the data on the dependent variable are transformed, the estimated relationship will differ from the true relationship. Furthermore, if the relationship between the two variables is simply static then the application of the seasonal-adjustment filter solely to the data on the dependent variable will succeed in making a dynamic model appear to be of relevance.

The simulation experiments which Wallis conducted were based upon two different forms of dynamic relationship between a dependent variable (y) and an explanatory variable (x): a geometric lag function; and an inverted-V-shape lag function. In this context, official adjustment of the data was undertaken.[85] The simulation results were seen largely to reinforce the theoretical findings of the study. For example, the

[84] The official method of seasonal adjustment was regarded as the U.S. Bureau of the Census Method II, Variant X-11, as modified by the British Central Statistical Office.

[85] For each experiment, 180 time-series observations on x were generated, and fifty replications were performed.

properties of estimators were observed to be superior when both of the series on x and y were subject to seasonal adjustment, rather than the series on y, alone.

In a subsequent paper, in the same volume of the *Journal of the American Statistical Association*, Sims (1974) too was concerned with the issue of seasonality and regression. Adopting the framework of a bivariate distributed-lag model, consideration was initially given to the implications for the properties of estimators of the presence of seasonal noise in the data. Sims then examined the consequences for asymptotic bias of applying different forms of seasonal adjustment.

In particular, in Section 4 of Sims' paper, there occurred a discussion of the impact of utilising published seasonally-adjusted data. Attention was drawn to the potential problem of the method of adjustment not fully succeeding in eliminating all of the power at the seasonal frequency. However, in common with Wallis (1974), Sims supported a reliance upon a common filter. The justification which he provided was that the bias will remain unchanged from when analysing unadjusted (contaminated) data, while seasonal frequencies are ignored in estimation.[86]

Ghysels has been, at least in part, responsible for several studies which have sought to address the issue of the effect of seasonal-adjustment procedures on the properties of statistical tests. More specifically, the papers by Ghysels (1990) and Ghysels and Perron (1993) examined the implications of seasonal adjustment for the outcomes of unit root tests. In the earlier of the two articles, unit root tests were performed in conjunction with both seasonally-adjusted and seasonally-unadjusted post-war

[86] Sims regarded the effects of seasonal noise on the properties of estimators as a form of errors-in-variables problem.

quarterly time series on U.S. G.N.P.. The analysis of the adjusted data enabled a clear inference to be drawn of the presence of a unit root. In contrast, though, from a consideration of the unadjusted data, there occurred less conclusive results.[87]

Ghysels and Perron (1993) investigated the consequences of seasonal adjustment within univariate dynamic regression models. In particular, the focus of attention was on the properties of the Ordinary Least Squares estimator of the sum of the autoregressive coefficients. In the absence of a unit root, where data had been subjected to the X-11 filter, the estimator was seen to be asymptotically upwards biased. In contrast, in the presence of a single unit root, the Ordinary Least Squares estimator was found to be consistent. Ghysels and Perron proceeded to perform an extensive simulation study which enabled them to establish the finite-sample properties of Dickey-Fuller and Phillips-Perron unit root tests. They discovered that, in many cases, the use of seasonally-adjusted data resulted in a substantial reduction in power, compared to situations where data had not been filtered. Ghysels and Perron maintained that the findings of their research provided support for the argument that annual data should be relied upon when conducting a test for a unit root.

In a subsequent study, Ghysels and Perron (1996) assessed the effects of two-sided linear filtering in the context of models which allowed for structural change. More specifically, they undertook both theoretical analysis and Monte Carlo simulations

[87] The study by Jaeger and Kunst (1990) was also founded upon an analysis of time-series data on U.S. G.N.P.. Their investigation showed that the series which was the outcome of the X-11 method of seasonal adjustment was associated with a greater degree of persistence than time series which had been deseasonalised using alternative procedures.

with the objective of determining the statistical properties of unit root tests and tests for parameter stability.

In Section 4 of their paper, Ghysels and Perron carried out a large-sample analysis. Adopting the framework of a model which admits a change in the slope of the linear trend, the limiting distribution of the unit root test statistic was found to be the same, irrespective of whether the data were contained in a raw or an adjusted form. Having proceeded to assume that the alternative hypothesis (of a stationary time series) is true, Ghysels and Perron discovered the test statistic which was founded upon the adjusted data to be asymptotically biased. However, the extent of the bias was observed to be no greater than when no break in the trend line is permitted.[88]

Concerning tests for structural change, the linear approximation to the X-11 procedure was seen to be responsible for creating size distortions. To be more precise, the application of the filter succeeded in producing oversized tests. Further investigation revealed that the impact on the power of a stability test of attempting to remove seasonal variation in the data is relatively small. Also, gains as well as losses are possible, with the timing of the break-point appearing to be fundamental to the outcome.

The design of the Monte Carlo experiments and the associated results were reported in Section 5 of the Ghysels and Perron paper. Data-generating processes were specified so as to incorporate a structural break half of the way through the sample period. Ghysels and Perron regarded their most important finding to have been that,

[88] This result depended upon the number of periods which were covered by the seasonal-adjustment polynomial remaining fixed, while the sample size altered.

with respect to the power of a unit root test, no benefit was derived from attempting to capture seasonal behaviour through the use of dummy variables. Instead, a standard process of filtering or applying an augmentation to the autoregressive element of the model appeared to be more productive, with the latter having been observed to have a slight edge over the former. In relation to tests for parameter stability (where the position of the break-point was assumed to be unknown), in some cases, filtering was seen to be responsible for modest size distortions. Also, this approach towards seasonal adjustment was found to exert an adverse influence on the power of a stability test, albeit, not as pronounced as for a unit root test.

A final study on the topic of seasonality to involve Ghysels consists of the research which he performed together with Lee and Siklos (Ghysels *et al*. (1993)). The aim of this paper was to investigate whether or not spurious seasonal fluctuation arises from attempting to extract seasonality from a time series using a method of adjustment which corresponds to a misspecified model of seasonal behaviour.

Five different transformations were applied to twenty-four U.S. quarterly time series, which usually extended from 1946 to 1989. Ghysels *et al*. followed the procedure which was advocated by Hylleberg *et al*. (1990) for the purpose of assessing whether or not unit roots are present at seasonal and zero frequencies. The results which were obtained appeared to confirm the neutrality of the X-11 method with respect to its effect on the occurrence of a unit root. However, one of the conclusions of this study was that a limitation of standard approaches towards the removal of seasonality is their failure to accommodate changing seasonal patterns over time. Also, whichever transformation was implemented appeared to have implications for non-seasonal variation.

The paper by del Barrio Castro *et al*. (2002) sought to extend the earlier study of Ghysels and Perron (1993). More specifically, consideration was given to the performances of three unit root tests when applied to data which were obtained using two different signal extraction procedures, rather than the original time series. The three unit root tests consisted of the augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test. The two methods of achieving the trend-cycle component of a series were the ARIMA model based and modified airline filter procedures.[89] The conclusions which were reached by del Barrio Castro *et al*. were founded upon the results of both an asymptotic analysis and simulation experiments.

From their theoretical investigation, which was undertaken assuming the use of filtered time series, del Barrio Castro *et al*. found that, in the presence of a unit root, the estimators of the first-order autoregressive parameter were asymptotically unbiased. In contrast, in the absence of a unit root, a non-negligible degree of bias was discovered, which was always in a positive direction.

The Monte Carlo exercise involved generating data through the means of nine different time-series processes. For both forms of adjustment filter and each of the ADF and PP tests, it could be observed that the empirical power probability was below the corresponding figure for the unadjusted data. In the case of the KPSS test,

[89] ARIMA denotes Autoregressive Integrated Moving Average.

there occurred the general problem of a too frequent rejection of the null hypothesis when using filtered data.

del Barrio Castro also collaborated with Osborn for the purpose of investigating the effects of the X-11 adjustment procedure on the properties of periodic autoregressive processes (del Barrio Castro and Osborn (2004)). Both asymptotic analysis and simulation experiments were conducted, having allowed for quarterly time-series data to have been generated by eight different periodic autoregressive processes, five of which were stationary.

The asymptotic analysis showed that, with respect to a stationary process, the application of the linear approximation to the X-11 method was generally responsible for a bias in the direction of a unit root. Also, in the case of variables which have an order of periodic integration which is equal to one, seasonal adjustment was seen to create a process which possesses a conventional autoregressive unit root. The findings of the simulation exercise helped to produce a fundamental conclusion of this study, namely, that a reliance upon seasonally-adjusted data serves to reduce the extent of, but not to eliminate entirely, periodic fluctuation. It should be recognised that the X-11 procedure corresponds to a particular type of seasonality. Thus, if the actual seasonality is not exactly of this nature then it is to be expected that the data continue to exhibit seasonal variation.

From the summaries which have been provided above, it can be gleaned that seasonal adjustment has the capability of altering the statistical properties of a time series. In particular, evidence has repeatedly been produced which shows that seasonal adjustment has the effect of raising the probability of falsely inferring non-stationarity. The studies by Marrocu (2006) and Matas-Mir *et al*. (2008) have indicated other forms of distortion which may arise from performing analysis in conjunction with seasonally-adjusted data.

The objective of the paper by Marrocu was to investigate the consequences of different transformations for the non-linear properties of time-series processes. Results were obtained from having performed Monte Carlo experiments. More specifically, artificial time series were generated using threshold functions, the specifications of which were guided by empirical models which had been applied to quarterly data on the U.S. rate of unemployment over the period, 1960-1997.

In Section 4 of Marrocu's paper, consideration was given to the effects of seasonal adjustment on non-linear processes which were responsible for generating time-series data. Tests for linearity were conducted using unadjusted data, as well as time series which were produced through adopting three different approaches towards seasonal adjustment. The latter consisted of a regression-based, dummy variable method, seasonal differencing, and a reliance upon the Census X-12 procedure. From the simulations, Marrocu found that, when the data-generating process was a linear model, seasonal adjustment did not seem to disturb the properties of the series. In contrast, for all of the non-linear specifications, the rejection frequency which was founded upon the data that were achieved from the implementation of the X-12 programme was lower than that which corresponded to the unadjusted series. Moreover, the negative effect of seasonal adjustment was most marked in the context of a model in which the form of the seasonal variation was linked to the stage of the business cycle.

The aim of the study by Matas-Mir *et al*. (2008) was to consider the implications of seasonal adjustment for the properties of business cycle expansion and recession regimes. The method of seasonal adjustment which was employed was the linear version of the X-11 programme of the U.S. Bureau of the Census. Conclusions were produced which were based upon theoretical analysis, simulation experiments and an empirical examination of quarterly data on four coincident U.S. business cycle indicators.

An outcome of the analytical part of the paper was that, in general, seasonal adjustment reduces the gap between the two means for the respective regimes, with the consequence that a recession does not seem to be as deep as when observing unadjusted data. Also, it was found that the magnitude of a regime change at the actual turning points is diminished by the use of seasonally-adjusted data. The findings which emerged from the simulation experiments confirmed the analytical results. The Monte Carlo exercise showed that a dependence upon seasonally-adjusted data gives rise to a substantial underestimation of the degree of a downswing. Additionally, there occurs a tendency to overestimate the duration of a recession.

Within the empirical section of their paper, Matas-Mir *et al*. examined seasonally-adjusted and unadjusted quarterly U.S. data on G.D.P., industrial production, employment and sales over the period, 1953q1-2003q4. For all four of the variables, seasonally-adjusted data were seen to be associated with recessions which were distributed over a longer interval and were of a shallower nature than those which corresponded to the unadjusted data.

This section concludes by making reference to a study which has expressed concerns over a reliance upon conventionally seasonally-adjusted data. Moosa and Lenten (2000) recognised drawbacks from using the X-11 programme for the purpose of transforming data. They saw an advantage in adopting a model-based strategy towards eliminating seasonality to be that seasonal adjustment would be tailored to the characteristics of the respective time series. In particular, Moosa and Lenten favoured the adoption of Harvey's structural time-series modelling approach towards isolating the seasonal component of a time series.[90] For twenty-two monthly and quarterly Australian time series, a comparison was performed of the seasonal elements arising from the implementation of the X-11 and structural time-series modelling procedures. The clearest discrepancies were identified as being associated with the current account balance, total personal finance commitments, and lamb production.

3.5 Unit Root Tests/The Form in which Variables Enter the VAR Model

A key consideration when constructing an econometric model concerns the form in which to contain the constituent variables. Within the applied econometrics literature, when specifying a VAR model, there has been a tendency to enter each of the endogenous variables in a manner such that the associated time series is

[90] For an introduction to structural time series modelling, see Harvey and Shephard (1993).

stationary (e.g., Ferderer (1996), Jimenez-Rodriguez and Sanchez (2005)). Granger and Newbold (1974) performed Monte Carlo simulations for the purpose of demonstrating the potential to achieve spurious results from an Ordinary Least Squares (OLS) regression involving two time series, both of which were generated by a random walk process. In this context, unless the respective variables are cointegrated, the assumptions upon which a standard hypothesis test is based are violated. Hence, any inference which is drawn from, for example, the result of a t test is unreliable.

Consequently, in order to facilitate comparisons, as well as for statistical reasons, there is a preference for admitting the chosen variables to the VAR model in a form such that the corresponding time series are stationary. Two key questions which subsequently arise consist of:

- are any of the time series already stationary?
- If a time series is not stationary then what constitutes a suitable transformation to apply to the associated variable in order remedy this situation?

Both of these questions can be answered by conducting unit root tests. The most frequently performed unit root test is the augmented Dickey-Fuller (ADF) test. The precursor to the latter is the Dickey-Fuller (DF) test, which originates from the article by Dickey and Fuller (1979). If the time series which is being analysed relates to the variable, y, then a DF test can be undertaken by constructing the equation:

$$\Delta y_t = \gamma y_{t-1} + \varepsilon_t, \tag{3.5.1}$$

where $\{\varepsilon_t\}$ denotes a sequence of independently, identically distributed random variables, each one of which has a population mean of zero and a variance of σ_ε^2.

The above equation is estimated using OLS, following which the value of a t statistic is computed with the objective of testing the null hypothesis, Ho: $\gamma = 0$, against the one-sided alternative hypothesis, Ha: $\gamma < 0$. Unfortunately, on the basis that the null hypothesis is true, the asymptotic distribution of the constructed statistic is not the standard t distribution, hence, the usual critical values do not apply. Having performed Monte Carlo simulation experiments, Fuller (1976) provided critical values which are of relevance for this type of situation. However, within this thesis, a preference is displayed for relying upon critical values which have been produced by MacKinnon (1996), given that these have been founded upon a greater number of replications.

Should the computed value of the t statistic be less than the corresponding critical value then, at the appropriate level of significance, Ho is rejected in favour of Ha, and the inference is drawn that the series on y is stationary. Equivalently, the verdict is reached that the variable, y, is integrated of order zero (y ~ I(0)). However, in contrast, suppose that, from the application of DF tests, it is not possible to infer that the series on y is stationary, yet, for the series on the first-difference of the variable, Ho can be rejected in favour of Ha. Here, the pronouncement would be made that y is integrated of order one (y ~ I(1)). More generally, if, from separate analyses, the suggestion is that the first-difference operator needs to be applied to y as many as d times in order to achieve a stationary time series then y would be declared as being integrated of order d (y ~ I(d)).[91]

Dickey and Fuller (1979) extended equation (3.5.1) to produce three different contexts in which a DF test can be performed: a model which includes neither an intercept nor a deterministic trend term; a model which includes an intercept but excludes a deterministic trend term; and a model which includes both an intercept and a linear deterministic trend term. Whichever of the three frameworks is adopted, the procedure for conducting the DF test is precisely the same. However, it must be respected that the probability density function of the t statistic is sensitive to not only the sample size but also the deterministic terms which enter the test equation. Consequently, a different set of critical values needs to be consulted in each of the three scenarios.

An inspection of relevant tables shows that, for a given level of significance, when expressed in absolute terms, the critical value decreases as the sample size becomes larger. Also, for a given level of significance and sample size, the magnitude of the critical value increases as the deterministic terms are added to the test equation. The varying nature of the probability density function of the DF t statistic has the implication that should the test equation be overspecified, for example, through needlessly including a deterministic trend, then the probability of rejecting a false null hypothesis would be reduced. On the other hand, though, should the equation for Δy_t be underspecified, e.g., by erroneously omitting the linear trend term, then Perron

[91] A study of the empirical literature suggests that most macroeconomic variables are I(1) and none have an order of integration which is in excess of two.

(1988) has demonstrated that the power of the DF test approaches zero as the sample size increases.

Formal procedures have been proposed (e.g., by Dolado *et al*. (1990)) for the purpose of deciding upon the deterministic terms to accommodate within the test equation. In practice, though, such approaches seem to have been largely ignored. A familiar practice is to perform unit root tests within all of the different contexts, without discrimination (e.g., Jimenez-Rodriguez and Sanchez (2005)). Within this thesis, the preference is for adopting a simple methodology which is founded upon an observation of a time plot of the relevant variable. To be more precise, if, from a study of the line graph, the value of the variable displays a tendency to increase or decrease over time then the most general model is regarded as suitable. In the apparent absence of any trending behaviour, a specification which excludes the deterministic trend term is considered appropriate. The perceived relevance of the intercept term is then governed by the value of the sample mean of the variable. More specifically, a value of the sample mean which is in the vicinity of zero is deemed to excuse the need for an intercept term to be present in the test equation. Otherwise, the recommendation is the retention of the constant component.

The legitimacy of the critical values relating to the DF tests for a unit root which have been discussed so far rests upon the assumption that the error terms in the respective equation are independently and identically distributed. Consequently, in a situation of serially correlated disturbances, these critical values cease to be valid. There exist two broad approaches towards addressing the problem of autocorrelated error terms. A non-parametric response was favoured by Phillips (1987) and Phillips and Perron (1988), which involved modifying the original DF statistic to accommodate consistent estimators of unknown variances. In contrast, Dickey and Fuller (1979) and Said and Dickey (1984) elected to follow a parametric route which consisted of extending the test equation to include a number of lags, p-1 (> 0),[92] on the dependent variable. Hence, the *augmented* Dickey-Fuller (ADF) regression equation can be presented as:[93]

$$\varDelta y_t = \gamma y_{t-1} + \sum_{i=2}^{p} \lambda_i \varDelta y_{t-i+1} + \varepsilon_t. \tag{3.5.2}$$

The second strategy has been popularly adopted when analysing macroeconomic time-series data. Hence, in the empirical chapters of this thesis, ADF tests are performed in conjunction with all of the quarterly time series corresponding to variables which enter the VAR model. The ADF test is conducted in precisely the same manner as the DF test, hence, is appropriate for assessing the suitability of Ho: $\gamma = 0$ against Ha: $\gamma < 0$. Indeed, it should be appreciated that, when the null hypothesis of a unit root is true, the distribution of the ADF t statistic is identical to that of the DF t statistic. The explanation for this result is that, when a variable which is I(1) is residing alongside variables which are I(0), on the right-hand side of an equation, the asymptotic distribution of the OLS estimator of the respective

[92] Underpinning an equation which incorporates p-1 lags on Δy is a pth-order autoregressive process for describing the behaviour of y.
[93] This equation has been specified so that it does not contain either an intercept or a trend term. However, as was the case earlier, the equation can be extended to accommodate deterministic regressors.

parameter is independent of the distributions of the estimators of the parameters which are connected to the stationary time series.[94]

A decision which it is necessary to take, when conducting an ADF test, concerns the number of lags, (p-1), to include on the dependent variable in the test equation.[95] A commonly used approach consists of setting the maximum number of lags in compliance with a credible rule. For example, within the article by Schwert (1989), there is to be found the formula, Int.$\{12(T/100)^{1/4}\}$, where T denotes the sample size.

Having established this upper limit, the optimal value of p-1 can be determined in different ways. One possibility is to choose the value of p-1 which succeeds in minimising the value of an information criterion. Two frequently encountered criteria are the Akaike information criterion (AIC) and the Schwarz Bayesian information criterion (BIC). Both are constructed in order to reward parsimony and a good fit of the sample data. Different definitions of the AIC and BIC can be found within the econometrics literature. The software package, *EViews*, which is relied upon for producing empirical results in this thesis, computes values on the basis of the following expressions:

$$AIC = -2(\log.L)/T + 2k/T; \qquad (3.5.3)$$

$$BIC = -2(\log.L)/T + k(\log.T)/T. \qquad (3.5.4)$$

[94] Additionally, it should be recognised that an examination of the validity of individual restrictions which are imposed upon λ_i (i = 2, 3, …… , p) can be performed through using a conventional t test.

[95] Whatever method is relied upon for determining the optimal number of lags, it is essential for the behaviour of the error terms in the favoured model to accord with a white noise process.

Regarding the above definitions, log.L denotes the value of the logarithmic form of the likelihood function, while k indicates the number of parameters in the corresponding equation that have been estimated.

As an alternative to selecting the value of p-1 on the basis of an information criterion, the scope exists to apply a sequential rule. For example, it is possible to implement a general-to-specific procedure. The latter entails initially specifying and estimating a model which features the maximum number of lags on the dependent variable. An investigation is then undertaken of whether or not a smaller number of lags is statistically acceptable. More specifically, the estimate of the parameter which is attached the longest lag is examined. Should this be found to be statistically insignificant then the associated variable is discarded and estimation is performed in conjunction with a model which contains one less lag on the dependent variable. Again, the estimate of the parameter which is connected to the longest lag is subsequently scrutinised. Once more, should the estimate be seen to be statistically insignificant then the corresponding variable is eliminated and estimation follows of the resultant smaller model. The procedure continues in this manner, terminating on the first occasion upon which, at a conventional level, the estimated parameter which is subject to consideration is significant.[96]

Ng and Perron (1995) undertook Monte Carlo simulations for the purpose of comparing the merits of rival approaches towards determining the optimal number of lags on the dependent variable in an ADF regression equation. Their results showed a tendency for the AIC and BIC to favour models with a smaller number of lags. As a

[96] In the situation in which the data-generating process is a pure autoregressive model, this procedure will yield the true lag length with an asymptotic probability of one (on condition that the true number of lags does not exceed the chosen maximum).

consequence, these models were associated with large size distortions, especially when a moving average process was responsible for the data. In contrast, the general-to-specific procedure seemed prone to selecting models with longer-length lags. While a consequence of the latter feature was a lower degree of power, the empirical size of the ADF test was nearer to its nominal level. Research which was carried out by DeJong *et al*. (1992a) has also provided support for the testing-down methodology. This showed that an increase in the number of lags produces only a modest decrease in power, yet a much more substantial reduction in size distortion.

Unfortunately, those tests which have been in widespread use for the purpose of assessing whether or not a stochastic process contains a unit root have been observed to be associated with non-negligible statistical problems. Two major weaknesses consist of a low degree of power and the empirical size of the test not equating with its nominal size. There have been many unit root tests which have been suggested, which are considered to be improvements upon the ADF and PP tests.[97] Although there is not one of these more recent tests that has developed the reputation of being unambiguously superior, the recommendation which was made by Maddala and Kim (1998, p. 99) was that ADF and PP tests should be discarded in favour of these tests.

Schwert (1989) performed Monte Carlo simulations for the purpose of indicating the size distortions corresponding to popularly adopted unit root tests. He showed that the probability distributions of DF statistics differed markedly from those which had been presented by Dickey and Fuller (1979) when the error term behaved in

[97] For a discussion of several of these, see Chapter 4 of the book by Maddala and Kim (1998).

accordance with a moving average process. Schwert also found PP tests to be subject to size distortions in the presence of a large moving average parameter.

In contrast, the concern of DeJong *et al*. (1992a) was with the lack of power of unit root tests. They argued that unit root tests have lower power when the alternative hypothesis asserts that the data are the outcome of a trend-stationary process. In a second study, DeJong *et al*. (1992b) conducted simulations in order to examine the statistical properties of ADF and PP tests. Given the alternative hypothesis of a trend-stationary time series, the power of the PP tests was generally less than 0.10. Although the power of the ADF tests approached one-third, the verdict was reached by DeJong *et al*. that unit root tests required developing that have a greater capability of rejecting a false null hypothesis.[98]

There have been observed two general responses to the statistical problems which have been identified with the often-used ADF and PP tests. One approach has consisted of applying a modification to the respective statistic. An alternative strategy has been to devise an entirely new test.

Perron and Ng (1996) elected to augment the earlier PP test statistics with the objective of reducing the size distortions which were a feature of familiar unit root tests in the presence of negative values of moving average coefficients. In section 2 of their paper, they undertook Monte Carlo simulation experiments, involving one thousand replications, in order to contrast the exact sizes of unit root tests under different conditions. From a study of Table 1 (p. 439), it was possible to observe that,

[98] The problems of size distortion and low power of DF-type tests have also been recognised by Agiakoglou and Newbold (1992).

when the value of the moving average parameter was negative, PP tests were too liberal. The same general statement could be made about the ADF t test, although the extent of the size distortion was less in this case. However, an examination of Table 2 (p. 440) showed that, when reliance was placed upon the autoregressive spectral density estimator for the purpose of computing values of the modified (PP) test statistics, the empirical sizes of the corresponding tests were quite close to the nominal size of five per cent.

Subsequent asymptotic analysis and simulations which were performed by Perron and Ng enabled them to conclude that the extensions which were applied to the original PP statistics succeeded in delivering more robust tests of the unit root hypothesis. More specifically, in the case of negative values of moving-average parameters, the modified PP tests were found to have much superior size to and higher power than the ADF t test. Given positive-valued autoregressive coefficients, the modified tests possessed comparable size but greater power. Although, in the circumstance of a negative value of the autoregressive coefficient, the power of the ADF test exceeded that of a modified test, Perron and Ng drew consolation from the fact that such an eventuality was rare.

In order to address the statistical problems which had been identified with earlier procedures, the preference of Elliott *et al*. (1996) was to devise a completely new unit root test. In their study, Elliott *et al*. were able to demonstrate a benefit to be gained from adopting an approach which involved prior detrending of the data through performing a Generalised Least Squares (GLS) regression.

In section 2 of their paper, Elliott *et al*. derived the asymptotic power envelope for point-optimal tests of a unit root.[99] Subsequently, consideration was given to a class of tests which were asymptotically point optimal invariant.[100] A test which is point optimal has a power function which is tangential to the corresponding power envelope at one point. In the absence of a deterministic element in a model, the properties of the DF t test did not enable this to qualify as point optimal. Nevertheless, the computations which were undertaken by Elliott *et al*. showed that the behaviour of this test accorded with that of a member of the family of point-optimal tests.[101]

In the presence of a deterministic component in a model, the findings of Elliott *et al*. were very different. More specifically, within their paper, Figure 2 and Figure 3 (p. 823 and p. 824, respectively) indicated that unit root tests, which were founded upon OLS estimates of the relevant parameters, possessed power functions which were located well below the corresponding power envelopes.

The root cause of the inadequacy of the DF t test appeared to be the inefficient estimates of the parameters entering the deterministic section of the model. Consequently, Elliott *et al*. advocated conducting a form of GLS regression. This involved initially applying a common transformation to the variable which was under investigation and the deterministic regressors, i.e., the constant and linear trend term.

[99] The asymptotic power envelope is obtained by plotting the power of the optimal test against the specified value of the relevant parameter on the basis of the alternative hypothesis.
[100] The implication of a test being invariant is that the distribution of the associated statistic is unaffected by the nature of the deterministic component of the model.
[101] The same observation was made of the non-parametric tests which were formed by Phillips (1987) and Phillips and Perron (1988).

Following the transformations, the variables, y*, const* and trend* were created, which are defined below:

$$y_1^* = y_1, \tag{3.5.5}$$

$$y_t^* = y_t - \rho y_{t-1}, \qquad t = 2, 3, \ldots\ldots, T; \tag{3.5.6}$$

$$constant_1^* = 1; \tag{3.5.7}$$

$$constant_t^* = 1 - \rho, \qquad t = 2, 3, \ldots\ldots, T; \tag{3.5.8}$$

$$trend_1^* = 1; \tag{3.5.9}$$

$$trend_t^* = t - \rho(t-1), \qquad t = 2, 3, \ldots\ldots, T. \tag{3.5.10}$$

Regarding the above definitions, ρ constitutes an autoregressive parameter to which Elliott *et al*. assigned a value in order to achieve a power of approximately 0.5, in conjunction with a conventional level of significance. In general, $\rho = 1 + c/T$. For a model which includes an intercept but no deterministic trend term, c was set equal to –7.[102] In contrast, in the presence of additionally a linear trend term, the chosen value of c was –13.5.

Estimates of the values of the parameters which were incorporated within the deterministic part of the model were generated by performing an OLS regression of y^*_t on $constant^*_t$ and (if necessary) $trend^*_t$ (t = 1, 2, ………, T). These estimates were then used as a basis for detrending the time series on y. Finally, Elliott *et al*. applied an ADF t test to the detrended series, without the inclusion of any deterministic element in the associated equation. For the linear trend case, Elliott *et al*. produced critical values (Table 1, p. 825), which were appropriate for T = 50,

[102] Of course, in this situation, *trend** does not enter the analysis.

100, 200, ∞.[103] For a model which accommodates an intercept but not a trend term, it was maintained that suitable critical values correspond to those which are consulted when conducting a DF test in the context of an equation without a deterministic element.

The procedure which has been outlined above is referred to as a DF-GLS test. Figure 3 (p. 824) in the paper by Elliott *et al*. showed that, for a model including a trend term, the power function of the DF-GLS test was indistinguishable from the power envelope. From simulations which were designed to investigate the small-sample properties of unit root tests, Elliott *et al*. discovered that, in almost all cases, the DF-GLS test was associated with a higher power than the DF test. In particular, the superiority of their newly formed test was seen to be most marked for a model which featured an intercept but not a linear trend term.

At the same time as Elliott *et al*. (1996) were performing their investigation, Hwang and Schmidt (1996) were independently conducting a study which was also to reveal a benefit from undertaking a unit root test in conjunction with residuals which were the outcome of a GLS regression. More specifically, the purpose of the paper by Hwang and Schmidt was to propose new tests of the null hypothesis of a unit root against an alternative hypothesis which maintains that the time series which is subject to examination is trend stationary. Hwang and Schmidt compared the statistical properties of three unit root tests. Two of these were founded upon the application of GLS estimation to a model including an intercept, a linear trend and a

[103] For other sample sizes, note that *EViews* relies upon interpolation to acquire critical values.

random term.[104] One took the form of a coefficient-based test, while the other required the computation of the value of a t statistic. Consideration was also given to the Dufour-King (1991) point optimal invariant test. Note that there was a necessity for two versions of each one of the three tests, on account of different assumptions which were made about the initial value of the stochastic term in the aforementioned model.

Monte Carlo simulations were first performed, assuming the null hypothesis to be true. Specifically, twenty-five thousand replications were undertaken in order to establish the finite-sample probability density functions of the test statistics. The critical values which are incorporated in Table 1 (pp. 235-237) of their paper were then employed by Hwang and Schmidt for the purpose of determining the power of a unit root test under different circumstances.

The results of the simulations which were conducted with the objective of establishing the powers of the unit root tests were presented in Tables 2-8 (pp. 239-245) of the article. The power of a test was found to be sensitive to the sample size, the assumed and the true values of the autoregressive parameter, as well as the treatment that was given to the initial value of the stochastic term. The probabilities that are contained in these tables enabled the general conclusion to be reached by Hwang and Schmidt that GLS-based tests are superior to both Dickey-Fuller tests and the tests of Bhargava, Schmidt and Phillips. Additionally, the power of a GLS-

[104] It should be respected that when the autoregressive parameter which is fundamental to the GLS regression is allocated a value of zero then the GLS-based test amounts to a Dickey-Fuller test. Also, when the value of this parameter is set equal to one, the GLS-based test corresponds to a unit root test which was devised by Bhargava, Schmidt and Phillips. (See, for example, the papers by Bhargava (1986), Schmidt and Phillips (1992) and Schmidt and Lee (1991).)

based test appeared to be in accordance with that of the comparable Dufour-King test.

In a subsequent paper, Burridge and Taylor (2000) argued that the additional power of the DF-GLS test did not stem entirely from the increased efficiency of the estimates of the parameters entering the deterministic part of the model. Results which were obtained from simulation experiments showed that, even in a situation in which the GLS estimator of the constant term was less reliable than the OLS estimator, the power of the DF-GLS test exceeded that of the DF test.[105] The more pertinent explanation for the extra power of the DF-GLS test involved the shifts which were observed of the null and alternative distributions. To be more specific, a consequence of relying upon GLS estimation was that the null distribution of the test statistic was moved much closer to the origin than was the alternative distribution.

Research which was undertaken by Ng and Perron (2001) also indicated how the properties of a unit root test could be enhanced by performing a GLS regression when seeking to eliminate the deterministic component from a time series. Additionally, this study contained a proposal for implementing unit root tests in conjunction with modified versions of conventional information criteria.

As was mentioned earlier in this section, Perron and Ng (1996) adapted the unit root tests, which had been suggested by Phillips (1987) and Phillips and Perron (1988), to produce tests which were subject to significantly smaller size distortions in the presence of negative moving average coefficients. Ng and Perron (2001) elected to

[105] In particular, see Table 1 (p. 638) and Table 2 (p. 639) within the paper by Burridge and Taylor.

extend these modified tests such that detrending was founded upon GLS estimation. Simulation experiments which were conducted showed the newly constructed tests to be uniformly more powerful than their predecessors. Furthermore, they possessed local asymptotic power functions which were indistinguishable from the function which was associated with the DF-GLS test. Ng and Perron proceeded to advocate that a further class of unit root tests be created by estimating the autoregressive spectral density using detrended data which were the outcome of a GLS regression.

Within their study, Ng and Perron maintained that the traditionally used AIC and BIC did not accurately reflect the cost of underfitting. Hence, they recommended modified forms of these criteria (MAIC and MBIC, respectively) which were specified such that the cost of overfitting was not a linear function of the number of lags on the dependent variable.[106] Simulation experiments were performed by Ng and Perron which involved the application of the DF-GLS test and one of their most recently proposed tests. The results showed that, in general, the new information criteria were superior to the established criteria in terms of choosing a number of lags for which the empirical size of the test was close to its nominal size.

In section 7 of their paper, Ng and Perron compared the statistical properties of ten unit root tests. Their findings suggested that, with respect to the power of a unit root test, there were gains to be achieved from adopting GLS estimation in order to detrend the data. Also, when conducting a DF-GLS test, it was generally preferable to choose the number of lags in accordance with the MAIC.

[106] Definitions of the MAIC and MBIC can be found on p. 1529 of the paper by Ng and Perron.

In the penultimate section of their paper, Ng and Perron analysed quarterly time series, extending from 1960q2 to 1997q2, on the annualised inflation rates for the G7 countries.[107] Five different unit root tests were performed, using both the BIC and the MAIC for deciding upon the number of lags. The results showed that a reliance upon the MAIC encouraged the choice of a longer lag length. Also, a dependence upon the MAIC usually produced weaker evidence that the time series was stationary.

3.6 Analysis Performed in Conjunction with a VAR Model

3.6.1 Introduction

The key feature of a VAR model is that feedback is permitted between all of the variables which enter the system. In the most basic form of the model, all of the variables are treated symmetrically. *A priori*, all of the variables are regarded as endogenous. Hence, it is unnecessary to make any distinction between dependent and independent variables.

A fundamental consideration when specifying and performing analysis in conjunction with a VAR model is the order of the latter, i.e., the maximum length of lag on the endogenous variables. Below, different approaches will be discussed towards determining the suitable lag length. One possibility consists of, having decided upon the longest lag which is feasible, respecting the impact of the number of lags upon the available degrees of freedom, to undertake sequential testing in order to discover whether or not a lower order of model is acceptable. An alternative

[107] In particular, an inflation rate was formed from the corresponding G.D.P. deflator.

approach is to make use of an information criterion. Information criteria are designed to penalise models which contain an excessive number of parameters and exhibit a poor fit of the sample data. Having estimated models of different orders over a common sample period, the system which is preferred is the one which is associated with the lowest value of the information criterion.

Following estimation of the favoured VAR model, various devices are typically employed which serve to aid the understanding of the interrelationships between the variables which enter the system. To be more specific, the estimated form of the model is popularly used as a basis for generating impulse responses, undertaking forecast error variance decompositions, and performing Granger-causality tests.

Any VAR model possesses a moving average representation. The vector moving average (VMA) model relates the current value of each of the endogenous variables to current and past values of all of the error terms which enter the equations of the corresponding VAR system. Hence, it permits the opportunity to trace the response over time of any of the endogenous variables to a shock to either itself or one of the other variables which resides in the model.

'Innovation accounting' is a descriptive term which refers not only to the production of impulse responses but also to the decomposition of forecast error variances. Utilising the moving average form of the VAR model, it is possible to attribute unexpected movements in an endogenous variable to current and past shocks to itself, as well as the other variables within the system. From an examination of the contributions, an indication can be obtained of the relative importance of the different variables within the system towards explaining the behaviour of the selected endogenous variable.

Within the context of the type of equation to be found within a VAR model, it is possible to define the concept of Granger-causality. Granger-causality is regarded as occurring when the explanation of the variation in the left-hand-side variable is significantly weakened by the omission from the equation of the lags on one of the other variables which enter the system. Of course, given the existence of a multiple-equation framework, there is an opportunity to investigate the presence of multiple Granger-causality. Testing for the latter involves an assessment of whether or not the lags on a designated variable are of relevance for determining any of the current values of the other endogenous variables within the system. This form of evaluation is sometimes referred to as a block exogeneity test.

3.6.2 The Concept of a VAR Model

At the beginning of this sub-section, the assumption is made that the objective is to investigate the interrelationships between n economic variables. Should there occur uncertainty over whether or not any of these variables are exogenous then the recommendation is initially to treat all of the variables as endogenous. The structural form of a VAR model, otherwise known as the primitive system, relates the current value of each of the n variables to not only past values of itself but also current and past values of all of the other variables entering the analysis.

Allowing for as many as p lags on each of the n variables, the system can be presented as below:

$$B_0 x_t = \Gamma_0 + \Gamma_1 x_{t-1} + \Gamma_2 x_{t-2} + \cdots + \Gamma_p x_{t-p} + \varepsilon_t. \qquad (3.6.2.1)$$

Regarding the above equation, x_t is a column vector which contains the current values of the n endogenous variables. B_0 is a coefficient matrix which is of order (n x n), for which all of the elements which appear on the principal diagonal are equal to 1. Γ_0 is a column vector that is comprised of constant terms, which is of order (n x 1). Γ_j (j = 1, 2, ………, p) are coefficient matrices which are of order (n x n). Finally, ε_t is a column vector that consists of n uncorrelated, white noise stochastic error terms.

Pre-multiplication of the above equation by B_0^{-1} enables the standard form of the VAR model to be achieved:

$$x_t = B_0^{-1}\Gamma_0 + B_0^{-1}\Gamma_1 x_{t-1} + B_0^{-1}\Gamma_2 x_{t-2} + \cdots + B_0^{-1}\Gamma_p x_{t-p} + B_0^{-1}\varepsilon_t. \qquad (3.6.2.2)$$

More succinctly,

$$x_t = A_0 + A_1 x_{t-1} + A_2 x_{t-2} + \cdots + A_p x_{t-p} + e_t, \qquad (3.6.2.3)$$

where $A_i = B_0^{-1}\Gamma_i$, i = 0, 1, 2, ……, p, and $e_t = B_0^{-1}\varepsilon_t$.

It is apparent that, within the standard form of the VAR model, the current value of an endogenous variable is related merely to past values of itself and the other endogenous variables which feature in the system. e_t constitutes an (n x 1) vector of error terms. By construction, each one of these error terms is a linear combination of the white noise disturbance terms within the vector, ε_t. Hence, each one of the error terms in the standard model possesses a zero mean and a variance which is constant over time. Although, by design, the error terms are serially uncorrelated, it should be appreciated that, across the n equations, they have the potential to be contemporaneously correlated.

3.6.3 Estimation and Order of the VAR Model

The form of the standard VAR model is such that the equations which comprise the system can be satisfactorily estimated individually using OLS. On the basis that the error terms are homoskedastic and non-autocorrelated then OLS estimators are consistent and asymptotically efficient. As mentioned above, it is a feature of the error terms that they are correlated across equations. However, there is no efficiency gain from applying the Seemingly Unrelated Regression procedure for the reason that the same set of explanatory variables is contained on the right-hand side of every equation.

A critical issue when specifying a VAR system concerns the order of the model. In general, the optimal lag length (p) is determined empirically. However, there is a choice between the implementation of a sequential testing procedure and a reliance upon an information criterion.

When using the econometric software package, *EViews*, it is possible to apply a sequence of modified likelihood ratio (LR) tests in order to infer the appropriate order of VAR model. More specifically, initially, a maximum length of lag is decided upon, which is to be denoted here by p^{max}. Adopting a common sample period, VAR models are estimated which are allocated orders which range from 1 to p^{max}. Consideration is given, first of all, to the least restricted model, which includes p^{max} lags on each of the endogenous variables. The test is conducted of the null hypothesis which asserts that all of the coefficients which are attached to the variables corresponding to a lag of p^{max} are equal to zero. For the purpose of performing the test, the value of the following LR statistic is computed:

$$LR = (T - np^{max})[\log.(|\Sigma_{Ho}|) - \log.(|\Sigma_{Ha}|)] \sim \chi^2(n^2). \qquad (3.6.3.1)$$

With respect to the above equation, $|\Sigma|$ signifies the determinant of the estimated variance-covariance matrix of the OLS residuals, aligned to the n equations. The subscript provides an indication of whether the calculation of the value of the determinant has been undertaken assuming the validity of the null or alternative hypothesis.[108] The recommendation of Sims (1980b) is followed in applying a small-sample modification, which amounts to including in the formula $(T - np^{max})$, as opposed to the more conventional, T.

The computed value of the LR statistic is contrasted with a suitable five per cent critical value, which is extracted from the table of the chi-square distribution. Should the computed value exceed the corresponding critical value then the null hypothesis

[108] The null and alternative hypotheses view VAR models of order p^{max}–1 and p^{max}, respectively, as being of relevance.

is rejected and the inference is drawn that p^{max} is the appropriate order of VAR model. In this situation, the test procedure terminates. In contrast, though, should the computed value of the test statistic be no greater than the corresponding critical value then the null hypothesis is not rejected. In this case, the procedure continues with the model of order $p^{max}–1$ fulfilling the role of the system, the validity of which is subject to investigation. The definition of the LR statistic in equation (3.6.3.1) is amended accordingly.

A formal comparison is undertaken of how well models of order $p^{max}–1$ and $p^{max}–2$ fit the sample data. At the five per cent level, if the computed value of the LR statistic is observed to be significant then the inference is drawn that lags of up to $p^{max}–1$ are required on the endogenous variables, and the sequential testing procedure is terminated. On the other hand, if the computed value of the LR statistic is smaller than the corresponding five per cent critical value then the verdict is reached that lags of length $p^{max}–1$ are unnecessary. Thus, the procedure advances with attention switching to the suitability of a VAR model which is of order $p^{max}–2$.

When applying this sequential testing methodology, in moving from one stage to the next, the order of the VAR system which is under consideration is always lowered by one. The procedure comes to a halt on the first occasion on which a null hypothesis is rejected. The optimal number of lags on the endogenous variables corresponds to the model which represents the favoured alternative hypothesis. However, it must be respected that, although, each individual LR test is performed at the five per cent level of significance, the overall size of the test will not be 0.05.

It should be appreciated that the implementation of the sequential procedure which has just been outlined can give rise to inconsistencies. For example, the possibility exists that the data support the choice of the VAR model which is of order $p^{max}–1$ over the rival which has an order of p^{max}. At the next stage, a preference could be exhibited for the system which has an order of $p^{max}–2$ over the competitor which has an order of $p^{max}–1$. However, were an LR test to have been undertaken with the intention of contrasting the performances of the models which possess the orders p^{max} and $p^{max}–2$ then there is no necessity that the restricted system would have been accepted.

As an alternative to basing the choice of the order of the VAR model on a sequential testing procedure, it is possible to place reliance upon an information criterion. In the context of a VAR system with feasible orders p = 0, 1, ………, p^{max}, the general design of an information criterion, C(p), is:

$$C(p) = \log.(\left|\Sigma_p\right|) + c_T(\varphi(p)). \qquad (3.6.3.2)$$

Regarding the above definition, $\left|\Sigma_p\right|$ denotes the determinant of the estimated form of the variance-covariance matrix of the OLS residuals corresponding to the n equations of the VAR(p) model. c_T is a term which depends upon the sample size, T, and distinguishes the specific criterion. Finally, φ(p) constitutes a function of the order p, which indicates the number of parameters to be estimated. The determinant, $\left|\Sigma_p\right|$, is a non-increasing function of p. In contrast, φ(p) is designed to be positively related to the order of the VAR system. The optimal lag length on the endogenous variables achieves a suitable balance between these two competing forces and conforms to the lowest value of the information criterion.

Specific information criteria which have been used in empirical studies include the Akaike Information Criterion (AIC), the Schwarz Information Criterion (BIC) and the Hannan-Quinn Information Criterion (HQIC). In the context of a VAR model of order p, the respective definitions are:

$$AIC(p) = \log.(|\Sigma_p|) + (2/T)pn^2; \tag{3.6.3.3}$$

$$BIC(p) = \log.(|\Sigma_p|) + (\log.(T)/T)pn^2; \tag{3.6.3.4}$$

$$HQIC(p) = \log.(|\Sigma_p|) + (2\log.(\log.(T))/T)pn^2. \tag{3.6.3.5}$$

Consequently, for all of the above criteria, $\varphi(p) = pn^2$, the number of parameters which are attached to the endogenous variables within the VAR model. In contrast, c_T is subject to variation, assuming the form of 2/T, (log.(T))/T and 2log.(log.(T))/T in the definitions of the AIC, BIC and HQIC, respectively.

For a sample size of at least T = 16, the chosen value of p according to the AIC can be no less than its value on the basis of the HQIC, which, in turn, is greater than or equal to the optimal number of lags as determined by the BIC. Under general conditions, as long as the true order of the VAR model lies within the range, 0, 1, ………, p^{max}, then, adopting either the HQIC or the BIC, as the sample size increases towards infinity, the preferred order of the VAR model converges upon the true order.[109] In contrast, the use of the AIC is responsible for overestimating asymptotically the correct number of lags on the endogenous variables.

3.6.4 Generation of Impulse Response Functions

Having specified and estimated the parameters of a VAR model, it is commonplace to examine the effects of shocks to the different variables which enter the system. This form of investigation is known as an impulse response analysis.

Earlier in this chapter, the standard VAR model was presented as:

$$x_t = A_0 + A_1 x_{t-1} + A_2 x_{t-2} + \cdots + A_p x_{t-p} + e_t. \qquad (3.6.2.3)$$

If the time series corresponding to the n endogenous variables are stationary then the VAR model has a Wold moving average representation of the form:

$$x_t = \mu + \sum_{i=0}^{\infty} \Theta_i e_{t-i}, \qquad (3.6.4.1)$$

where μ is an (n x 1) column vector which contains the mean values of the endogenous variables and Θ_i (i = 0, 1, ………, ∞) are coefficient matrices which are of order (n x n). In particular, $\Theta_0 = I_n$.

The (j, k) element of the matrix, Θ_i (which will be denoted by $\theta_{jk}(i)$) indicates the response after i time periods of the jth endogenous variable to a one unit innovation

[109] Both the HQIC and the BIC can be referred to as consistent.

to the kth endogenous variable. The plot of $\theta_{jk}(i)$ against i (i = 0, 1, 2, ………) produces a graph which represents the diagrammatic form of an impulse response function. It must be respected that, for a stationary process, $\theta_{jk}(i) \rightarrow 0$ as $i \rightarrow \infty$, for all j and k. Hence, the effect of a shock is not enduring, such that this can be described as transitory.

A complication which tends to arise when conducting an impulse response analysis is that the error terms which enter the equations of the standard VAR model are contemporaneously correlated. In order to permit an interpretation of the impulses, a transformation of the innovations is sought which is capable of achieving stochastic components which are orthogonal to one another. If the variance-covariance matrix of the error terms in the standard VAR model is denoted by Σ_e then the quest is for a non-singular matrix, P, which is of order (n x n) and has the property that $PP' = \Sigma_e$. In this case,

$$x_t = \mu + \sum_{i=0}^{\infty} \Theta_i P P^{-1} e_{t-i} \qquad (3.6.4.2)$$

or

$$x_t = \mu + \sum_{i=0}^{\infty} \Psi_i \varepsilon_{t-i}, \qquad (3.6.4.3)$$

where $\Psi_i = \Theta_i P$ and $\varepsilon_{t-i} = P^{-1} e_{t-i} \sim (0, D)$ (i = 0, 1, ……), and D constitutes a diagonal variance-covariance matrix.

The matrix, P, is not unique, hence, there are various options concerning its specification. A feature of a structural VAR analysis is that economic theory is consulted in order to decide upon the design of P. Alternatively, an approach which is in widespread use has consisted of constraining P to be a lower-triangular matrix which is founded upon a Cholesky decomposition of Σ_e. Indeed, when using the software package, *EViews*, it is possible to choose the inverse of the Cholesky factor of the respective residual variance-covariance matrix to be responsible for orthogonalising the impulses.

It should be respected that, for the purpose of undertaking a Cholesky decomposition, an ordering is required of the endogenous variables contributing to the VAR model. The consequence of a variable appearing first on the list is that there is attributed to this all of the effect of any common component. In the empirical analysis which follows, the sequence which is adopted accords with that which was favoured in the study by Jimenez-Rodriguez and Sanchez (2005). Thus, from most exogenous to least exogenous, the arrangement of the variables is: real G.D.P.; the real price of oil; price inflation; a short-term rate of interest; a long-term rate of interest; the real wage; and the real effective exchange rate. However, when generating impulse response functions, it is always advisable to attempt at least one alternative ordering of the variables to enable an examination of the sensitivity of the results which are obtained.

3.6.5 Forecast Error Variance Decompositions

In relation to a VAR model, a consideration of forecast errors can be productive in terms of highlighting relationships between the endogenous variables in the system.

Recall once again, the standard form of the VAR model,

$$x_t = A_0 + A_1 x_{t-1} + A_2 x_{t-2} + \cdots + A_p x_{t-p} + e_t, \qquad (3.6.2.3)$$

which has the moving average representation,

$$x_t = \mu + \sum_{i=0}^{\infty} \Theta_i e_{t-i}. \qquad (3.6.4.1)$$

It was established above that, through undertaking a Cholesky decomposition of the variance-covariance matrix of the error terms, Σ_e, it is possible to relate the current value of each of the endogenous variables to current and past values of disturbances which are orthogonal to one another:

$$x_t = \mu + \sum_{i=0}^{\infty} \Psi_i \varepsilon_{t-i}. \qquad (3.6.4.3)$$

If, h periods in the future, the true values of the endogenous variables are

$$x_{t+h} = \mu + \sum_{i=0}^{\infty} \Psi_i \varepsilon_{t+h-i} \qquad (3.6.5.1)$$

then the h-period-ahead forecast errors are

$$x_{t+h} - E_t x_{t+h} = \sum_{i=0}^{h-1} \Psi_i \varepsilon_{t+h-i}. \qquad (3.6.5.2)$$

In the case of there being n variables entering the VAR model, x_1, x_2, ………, x_n, then the h-period-ahead forecast error for the variable, x_j, is:

$$x_{j,t+h} - E_t x_{j,t+h} = \psi_{j1}(0)\varepsilon_{x1,t+h} + \psi_{j1}(1)\varepsilon_{x1,t+h-1} + \ldots + \psi_{j1}(h\text{-}1)\varepsilon_{x1,t+1} \quad (3.6.5.3)$$

$$+ \psi_{j2}(0)\varepsilon_{x2,t+h} + \psi_{j2}(1)\varepsilon_{x2,t+h-1} + \ldots + \psi_{j2}(h\text{-}1)\varepsilon_{x2,t+1}$$

$$+ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots$$

$$+ \psi_{jn}(0)\varepsilon_{xn,t+h} + \psi_{jn}(1)\varepsilon_{xn,t+h-1} + \ldots + \psi_{jn}(h\text{-}1)\varepsilon_{xn,t+1},$$

where $\psi_{jk}(i)$ denotes the (j, k) element of the matrix, Ψ_i, and $\varepsilon_{x1,t+h-i}$, $\varepsilon_{x2,t+h-i}$, ……, $\varepsilon_{xn,t+h-i}$ are the elements of the vector, ε_{t+h-i} (i = 0, 1, ……, h-1).

On the basis of the above equation, the h-period-ahead forecast error variance for x_j is:

$$\sigma_{xj}(h)^2 = \sigma_{x1}^2[\psi_{j1}(0)^2 + \psi_{j1}(1)^2 + \ldots\ldots + \psi_{j1}(h\text{-}1)^2] \quad (3.6.5.3)$$

$$+ \sigma_{x2}^2[\psi_{j2}(0)^2 + \psi_{j2}(1)^2 + \ldots\ldots + \psi_{j2}(h\text{-}1)^2]$$

$$+ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots$$

$$+ \sigma_{xn}^2[\psi_{jn}(0)^2 + \psi_{jn}(1)^2 + \ldots\ldots + \psi_{jn}(h\text{-}1)^2],$$

where σ_{xk}^2 = var.($\varepsilon_{xk,t+i}$) (k = 1, 2, ……, n; i = 1, 2, ……, h).

The proportion of the variance which is attributable to x_j, itself, is:

$$\sigma_{xj}^2[\psi_{jj}(0)^2 + \psi_{jj}(1)^2 + \ldots\ldots + \psi_{jj}(h\text{-}1)^2]/\ \sigma_{xj}(h)^2.$$

More generally, the proportion of the variance which is attributable to endogenous variable, x_k, is:

$$\sigma_{xk}^2[\psi_{jk}(0)^2 + \psi_{jk}(1)^2 + \ldots\ldots + \psi_{jk}(h\text{-}1)^2]/\ \sigma_{xj}(h)^2.$$

Consequently, an h-period-ahead forecast error decomposition has been undertaken. This shows the proportions of the unexplained variation in an endogenous variable which are attributable to shocks to both itself and the other endogenous variables which form the VAR system. Experience suggests that, for short forecast horizons, the fraction of the unanticipated behaviour for which a shock to the variable, itself, is responsible is close to one. However, as the forecast horizon is lengthened, the contribution which is made by the own innovation typically diminishes.

It is apparent from the preceding analysis that, in order to be able to perform forecast error variance decompositions, disturbances are required to be orthogonal to one another. Once more, in the forthcoming empirical analysis, this property is achieved through the application of a Cholesky decomposition to the variance-covariance matrix, Σ_e. It must be recognised that this form of constraint can exert a strong influence on the results for short forecast horizons. However, its effect usually becomes more benign as the forecast horizon is extended. The recommendation is to undertake variance decompositions for different values of h and to observe a convergence of the respective proportions.

3.6.6 Granger-Causality Testing

Having estimated a VAR model, it is usually of particular interest to give consideration to the issue of causality. Granger (1969) advanced a definition of causality which is of relevance when investigating the dynamic relationships between two or more variables. In the context of a two-variable model which contains the variables, x_1 and x_2, the latter can be pronounced as Granger-causing the former should historical information on x_2 be found to improve significantly the explanation of the variation in the current value of x_1, beyond that which is achieved using merely past values of x_1, itself.

In the case of a two-variable VAR model which is of order p, the constituent equations can be presented as:

$$x_{1t} = a_{10} + a_{11,1}x_{1,t-1} + a_{11,2}x_{1,t-2} + \ldots\ldots + a_{11,p}x_{1,t-p} \quad (3.6.6.1)$$
$$+ a_{12,1}x_{2,t-1} + a_{12,2}x_{2,t-2} + \ldots\ldots + a_{12,p}x_{2,t-p} + e_{1t};$$

$$x_{2t} = a_{20} + a_{21,1}x_{1,t-1} + a_{21,2}x_{1,t-2} + \ldots\ldots + a_{21,p}x_{1,t-p} \quad (3.6.6.2)$$
$$+ a_{22,1}x_{2,t-1} + a_{22,2}x_{2,t-2} + \ldots\ldots + a_{22,p}x_{2,t-p} + e_{2t}.$$

In order to perform a test of Granger-causality extending from x_2 to x_1, the following null and alternative hypotheses are constructed:

Ho: $a_{12,1} = 0$, $a_{12,2} = 0$, ………, $a_{12,p} = 0$;

Ha: at least one of $a_{12,i} \neq 0$, i = 1, 2, ………, p.

Analogously, for the purpose of testing for Granger-causality extending from x_1 to x_2, the null and alternative hypotheses which are shown below are assembled:

Ho: $a_{21,1} = 0$, $a_{21,2} = 0$, ………, $a_{21,p} = 0$;

Ha: at least one of $a_{21,i} \neq 0$, i = 1, 2, ………, p.

If both of the variables enter the VAR system in a manner such that the associated time series are stationary then a standard F distribution is permitted to form the basis of each of the tests. Adopting a conventional level of significance, when compared to the corresponding critical value, should the computed value of the F statistic necessitate a rejection of the null hypothesis then the outcome of the test is that Granger-causality is present.

If the assumption is now made that n (> 2) endogenous variables enter the VAR model then the equations which comprise the system can be shown as:

$$\begin{aligned} x_{jt} = a_{j0} &+ a_{j1,1}x_{1,t-1} + a_{j1,2}x_{1,t-2} + \ldots\ldots + a_{j1,p}x_{1,t-p} \\ &+ a_{j2,1}x_{2,t-1} + a_{j2,2}x_{2,t-2} + \ldots\ldots + a_{j2,p}x_{2,t-p} \\ &+ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ &+ a_{jn,1}x_{n,t-1} + a_{jn,2}x_{n,t-2} + \ldots\ldots + a_{jn,p}x_{n,t-p} + e_{jt}, \end{aligned} \tag{3.6.6.3}$$

(j = 1, 2, ……, n).

In order to assess whether or not x_k is responsible for Granger-causing x_j, assuming that both of the variables correspond to stationary time series, a standard F test may be conducted of:

Ho: $a_{jk,1} = 0$, $a_{jk,2} = 0$, ………, $a_{jk,p} = 0$ against

Ha: at least one of $a_{jk,i} \neq 0$, i = 1, 2, ………, p.

Once again, having chosen a conventional level of significance, should the computed value of the test statistic exceed the corresponding critical value then the verdict which is reached is that Granger-causality operates from x_k to x_j.

An extension of a Granger-causality test is a block exogeneity test. In the case of the latter, attention is not simply limited to whether or not knowledge of the historical behaviour of x_k serves to improve the explanation of the variation in the current value of a selected other variable, x_j. Instead, consideration is given to whether or not past information on x_k is of relevance for determining the current values of any of the other endogenous variables, x_j (j = 1, 2, ………, n; j ≠ k) in the VAR system.

With reference to equation (3.6.6.3) for x_{jt} (j = 1, 2, ………, n), the block exogeneity test amounts to a formal assessment of the validity of the null hypothesis,

Ho: $a_{jk,i} = 0$ (j = 1, 2, ………, n; j ≠ k; i = 1, 2, ………, p),

when contrasted with the alternative hypothesis, Ha: at least one of $a_{jk,i} \neq 0$ (j = 1, 2, ………, n; j ≠ k; i = 1, 2, ………, p).

In this situation, the null hypothesis is imposing restrictions across the equations of the VAR model. Consequently, it is appropriate to perform an LR test. The design of the LR test statistic, incorporating Sims' recommended small-sample correction, is similar to equation (3.6.3.1):

$$LR = (T - np)[\log.(\,|\Sigma_{Ho}|\,) - \log.(\,|\Sigma_{Ha}|\,)] \sim \chi^2((n-1)p). \qquad (3.6.6.4)$$

With respect to the above definition, $|\Sigma_{Ho}|$ signifies the determinant of the residual variance-covariance matrix, having imposed upon the parameters the restrictions entering the null hypothesis. $|\Sigma_{Ha}|$ represents the determinant of the residual variance-covariance matrix corresponding to the freely estimated VAR system. Finally, the number of degrees of freedom, (n-1)p, equates with the number of restrictions which comprise the null hypothesis.

3.7 Post-Sample Analysis

When comparing the empirical performance of competing econometric models, it is desirable to conduct a post-sample as well as a within-sample analysis. Ideally, consideration should be given to not only values of measures of goodness of fit and/or information criteria which correspond to the estimation period but also the quality of the forecasts that are produced. There exist several well-established summary statistics, the values of which allow an assessment of the merits of a series of predictions. Additionally, formal tests have been proposed of the null hypothesis that rival sets of forecasts have equal accuracy. Moreover, a literature has emerged which is devoted to the concept of forecast encompassing, i.e., the issue of whether or not the information content of a linear combination of forecasts exceeds that of an individual forecast.

Table 8.11 (p. 250), within *Applied Time Series Modelling and Forecasting* by Harris and Sollis (2003), makes reference to five measures which are commonly used for the purpose of evaluating the quality of a series of forecasts. These measures are defined in Table 3.7.1, which is presented below.

Table 3.7.1: Available Measures for Evaluating the Quality of a Series of Forecasts

Forecast Evaluation Measure	Definition
Mean Square Error	$MSE = \frac{1}{n}\sum_{t=T+1}^{T+n}(y_t - y_t^*)^2$
Mean Error	$ME = \frac{1}{n}\sum_{t=T+1}^{T+n}(y_t - y_t^*)$
Mean Absolute Error	$MAE = \frac{1}{n}\sum_{t=T+1}^{T+n} \mid (y_t - y_t^*) \mid$
Root Mean Square Error	$RMSE = \sqrt{\frac{\sum_{t=T+1}^{T+n}(y_t - y_t^*)^2}{n}}$
Median Square Error	*MedSE* = the squared error for which 50 per cent of the squared errors are greater than this value

With regard to the above table, it is assumed that the estimation period extends to t = T, such that the forecast interval ranges from t = T+1 to t = T+n. Thus, n is the number of forecasts which are generated. The actual and predicted values of the variable which is under consideration are denoted by y and y*, respectively.

It should be recognised that, viewed on its own, the value of a single summary statistic offers only limited information on the quality of a series of forecasts and the adequacy of the underlying econometric model. Indeed, Diebold and Mariano (1995) expressed their frustration with studies which sought merely to compare point estimates of predictive accuracy, thereby ignoring the issue of sampling variability. Consequently, in their paper, they proposed formal tests of the null hypothesis of equal accuracy of two competing forecasts. More specifically, an asymptotic test and two finite-sample tests were recommended. A virtue of the tests which were advocated was considered to be their widespread applicability, namely, in situations where forecast errors are non-Gaussian, are lacking the property of a zero mean, and are serially and contemporaneously correlated.[110]

The assumption is made that e_{it} (t = T+1, T+2, ..., T+n) and e_{jt} (t = T+1, T+2, ..., T+n) are two series of forecast errors. The respective loss functions are denoted by $g(e_{it})$ and $g(e_{jt})$. Consequently, the null hypothesis of equal forecast accuracy can be presented as Ho: $E[d_t] = 0$, where $d_t \equiv g(e_{it}) - g(e_{jt})$. Diebold and Mariano suggested an asymptotic test of the latter. In the context of one-step-ahead predictions, the related statistic, S_1, was formed by dividing the arithmetic average value of d over

[110] The finite-sample tests were specifically the sign test and Wilcoxon’s signed-rank test. For the reason that only the asymptotic test is applied in the subsequent empirical analysis which is contained in this thesis, no discussion ensues of the two finite-sample tests.

the forecast interval by its standard error (with no allowance for autocorrelation). Under the null hypothesis, S_1 has asymptotically a standard normal distribution.

Monte Carlo experiments were conducted by Diebold and Mariano in order to establish the finite-sample size of each of their proposed tests, as well as some extant tests of equal forecast accuracy. In performing simulations, the assumption was made of a quadratic loss function. The errors were drawn from both a Gaussian distribution and a Student's t distribution (corresponding to six degrees of freedom). Furthermore, the series of errors were allowed to be autocorrelated and contemporaneously correlated. The values of statistics were computed, consistent with two-steps-ahead forecasts being generated. At least five thousand replications were undertaken and the chosen level of significance was ten per cent.

From an observation of Table 4 (p. 140) of the article by Diebold and Mariano, it is apparent that, for a sample size, n, which is equal to 8 or 16, the S_1 test is oversized, irrespective of whether the errors have been drawn from a Gaussian or a fat-tailed distribution. The empirical size of the test seems reasonably close to its actual size for $n \geq 32$, while the performance of the test appears to be robust to the presence of serial and contemporaneous correlation.

The aforementioned weakness of the S_1 test of Diebold and Mariano (i.e., being subject to a quite serious size distortion for a moderate size of sample) provided Harvey *et al*. (1997) with an incentive to investigate whether or not an adjustment to the test was possible which would have the capability of improving its statistical properties. In fact, Harvey *et al*. proposed altering the way in which the test was conducted in two distinct respects.

Harvey *et al*. established that the expected value of the estimator of the variance of the sample mean of d which was employed by Diebold and Mariano differed from the value of the population variance by a multiple of $[n^{-1}(n + 1 - 2h + n^{-1}h(h - 1))]$, where h signifies the number of periods ahead to which the forecast applies. Consequently, they adapted the statistic, S_1, of Diebold and Mariano so as to include an approximately unbiased estimator of the variance, which succeeded in yielding the modified statistic:

$$S_1^* = S_1\sqrt{\frac{1}{n}(n + 1 - 2h + n^{-1}h(h - 1))}. \tag{3.7.1}$$

The second amendment which was suggested to the manner in which the Diebold-Mariano test was performed consisted of comparing the computed value of the S_1* statistic to a critical value which corresponds the Student's t distribution, with n – 1 degrees of freedom.

In an attempt to confirm the benefit which was derived from making these adjustments, Harvey *et al*. undertook simulations in relation to both the original and the modified version of the Diebold-Mariano test. Forecast errors were independently drawn from a standard normal distribution. A quadratic loss function was employed, such that $d_t = e_{it}^2 - e_{jt}^2$. Tests of a two-sided alternative hypothesis were conducted at the ten per cent level of significance.

On the basis of ten thousand replications of their Monte Carlo experiment, Harvey *et al*. discovered that, in terms of size, the modified form of the test outperformed the original Diebold-Mariano for all of the different combinations of h and n which were considered.[111] While the empirical size of the S_1* test was generally in excess of 0.10, Harvey *et al*. held the opinion that it should be reasonably acceptable to practitioners.[112]

Further inspection of their simulation results encouraged Harvey *et al*. to maintain that the redesign of the test statistic was a more important factor than the reliance on the Student's t distribution in terms of improving the size. However, from consulting Table 1 (p. 285), it is apparent that, for the combination, h = 1, n = 8, a superior outcome is achieved through comparing the computed value of S_1, rather than that of S_1*, with the ten per cent critical value corresponding to the t_{n-1} distribution.

Attention now turns to the concept of forecast encompassing, which is an issue that has concerned many researchers, e.g., Chong and Hendry (1986), Clements and Hendry (1993), Holden and Thompson (1997). When undertaking an investigation of forecast encompassing, one model operates as a base equation, which is used to generate predictions, and an assessment is formed of whether or not any additional information is contained in corresponding forecasts which are produced by a rival model.

In order to discuss this concept more formally, the assumption is made that there are two competing models, both of which are employed to predict future values of a

[111] Specifically, n ranged from 8 to 512, while h varied from 1 to 10.
[112] It was reported by Harvey *et al*. that, when errors were drawn from a t distribution, which is associated with six degrees of freedom, the conclusions of the study were unaltered.

variable, y. The actual values of y over the forecast interval are denoted by y_t (t = T+1, T+2, ..., T+n); the two series of forecasts are represented by y^*_{it} and y^*_{jt} (t = T+1, T+2, ..., T+n). A forecast error is calculated by subtracting the predicted value from the corresponding actual value. The two series of forecast errors are indicated by e_{it} and e_{jt} (t = T+1, T+2, ..., T+n).

Fair and Shiller (1990) have proposed a test for forecast encompassing which requires construction and estimation of the model,

$$y_t = a + b_1 y^*_{it} + b_2 y^*_{jt} + \varepsilon_t, \tag{3.7.2}$$

where ε_t is a stochastic error term.

It should be respected that in the situation in which neither of the two competing models includes useful information then the values of both b_1 and b_2 will be equal to zero and the estimate of the intercept parameter will correspond to the sample mean value of y_t. When testing the null hypothesis, $b_1 = 0$, an assessment is being formed of whether or not the forecasts of model i contain information which is additional to that which is incorporated within the intercept and y^*_{jt}. Similarly, a test of $b_2 = 0$ permits the inference of whether or not information which underpins the forecasts of model j is supplementary to that which is accommodated within the intercept and y^*_{it}.

The above framework makes allowance for forecasts which are biased. The following analysis is designed to produce an equation which relates, more specifically, to unbiased forecasts.

Upon subtracting y^*_{it} from both sides of the equation for y_t, there is obtained:

$$y_t - y^*_{it} = a + (b_1 - 1)y^*_{it} + b_2 y^*_{jt} + \varepsilon_t. \tag{3.7.3}$$

When the two forecasts are unbiased, a = 0 and $b_1 + b_2 = 1$. Imposing these restrictions delivers the equation:

$$y_t - y^*_{it} = b_2(y^*_{jt} - y^*_{it}) + \varepsilon_t. \tag{3.7.4}$$

It is possible to achieve an equation in terms of forecast errors by adding y_t to and subtracting y_t from the bracketed term:

$$y_t - y^*_{it} = b_2((y_t - y^*_{it}) - (y_t - y^*_{jt})) + \varepsilon_t, \tag{3.7.5}$$

which can be equivalently written as

$$e_{it} = b_2(e_{it} - e_{jt}) + \varepsilon_t. \tag{3.7.6}$$

Consequently, it would seem that if a regression is performed of e_{it} on the difference between the two forecast errors, $e_{it} - e_{jt}$, then a significant estimate of b_2 suggests that the forecast, y^*_{jt}, includes useful information which is not present in y^*_{it}.

Alternatively, an insignificant estimate of b_2 permits the inference to be drawn that the forecast, y^*_{it}, encompasses the forecast, y^*_{jt}.[113]

Harvey *et al*. (1998) expressed concern with the adoption of a conventional regression-based approach towards testing for forecast encompassing. They doubted that forecast errors would accord with a normal distribution, and maintained that these were more likely to be associated with a t distribution corresponding to a small number of degrees of freedom. In the situation in which forecast errors are more suitably described by a fat-tailed distribution, the regression-based test is not robust and can give rise to over-frequent rejections of the null hypothesis.

More specifically, Harvey *et al*. derived asymptotic results in connection with a regression-based test of the null hypothesis, Ho: $b_2 = 0$, against the alternative hypothesis, Ha: $b_2 > 0$. The findings related to one-step-ahead forecast errors which conformed to a t_6 distribution, but which were non-autocorrelated and possessed a zero mean. When the test was performed at the five (ten) per cent level of significance, utilising critical values pertaining to a standard normal distribution, the true asymptotic size was calculated to be 0.122 (0.182). For forecast errors which accorded with a t_5 distribution, the frequency of rejection was established as 0.171 (0.230).

The finite-sample size of the regression-based test was determined by simulations. Harvey *et al*. gathered series of errors from both t_6 and t_5 distributions. Ten thousand replications of each Monte Carlo experiment were performed. From conducting this

[113] Also, an acceptance of the null hypothesis, Ho: $b_2 = 0$, permits the inference that y^*_{it} is "conditionally efficient" with respect to y^*_{jt}. Such terminology has been used by Granger and Newbold (1973, 1986).

exercise, it was discovered that the problem of an oversized test became more severe as the number of sample observations increased.

Recognising the deficiency of the regression-based test, Harvey *et al*. sought a robust test of forecast encompassing. In the situation in which forecast errors are not normally distributed, the variance of the stochastic error term in the regression equation will be non-constant. Consequently, Harvey *et al*. recommended allowing for heteroskedasticity in estimating the variance of the estimator of the slope parameter, b_2. However, the suggestion was also made that the earlier-mentioned, modified version of the Diebold-Mariano test be performed, although, in the context of forecast encompassing, $d_t = e_{it}(e_{it} - e_{jt})$.

Simulations were undertaken, initially for h = 1, which showed both the Diebold-Mariano test, itself, and the modified version to have approximately the correct size for large values of n. For small samples, though, while there were circumstances under which the empirical size of a test deviated markedly from its true size, the amended form of the Diebold-Mariano test was found to be superior to its competitors.

Harvey *et al*. also conducted simulations for the purpose of computing size-adjusted powers for different tests of forecast encompassing. In terms of being able to reject a false null hypothesis, the modified version of the Diebold-Mariano test did not stand out as representing an improvement on the other tests that were under consideration. However, for the reason that its nominal size was relatively reliable, Harvey *et al*.

sought to recommend its application, giving emphasis to its performance when forecast errors are not normally distributed.[114]

The properties of the test of forecast encompassing that was proposed by Harvey *et al*. (1998) were later explored by Clark and McCracken (2001). Consideration was also given to two alternative tests of the same hypothesis, as well as three tests of equal forecast accuracy. Distinctive features of the study by Clark and McCracken were the assumptions that one-step-ahead forecasts were generated by *nested* linear models and estimates of parameters were the outcome of recursive regressions.[115]

More specifically, Clark and McCracken assumed the presence of two linear models, one of which represented a restricted version of the other, both of which were estimated by OLS. In connection with the issue of forecast encompassing, they focused upon the performances of three different tests. As mentioned above, one of these was the test which was recommended by Harvey *et al*. (1998) (which Clark and McCracken denoted by ENC-T). A second test consisted of a regression-based version of the latter, which had been suggested by Ericsson (1992) (which was labelled ENC-REG). The third test (ENC-NEW), which was advanced by Clark and McCracken, themselves, represented a modification of ENC-T. In particular, it was advocated that, in forming the test statistic, the sample covariance of e_{it} and (e_{it} - e_{jt}) should be divided by the mean square error corresponding to one of the

[114] In a subsequent study, Harvey and Newbold (2000) sought to extend the concept of forecast encompassing to k (≥ 2) forecasts. In this context, the null hypothesis asserts that a given forecast encompasses the remaining k-1 predictions. The asymptotic and finite-sample analysis showed that a standard F test was unreliable when forecast errors did not accord with a normal distribution. Hence, Harvey and Newbold were encouraged to nominate alternative tests. Their preferred test (MS*) was founded upon the adaptation of the Diebold-Mariano test, which had been performed by Harvey *et al*. (1998). However, it was accepted that a large sample was required in order to benefit appreciably from its application.

[115] In an earlier, unpublished paper, Clark and McCracken (2000) allowed for both estimation over a fixed interval and rolling regression.

forecasts (i.e., y_{jt}*). Hence, mathematically, the ENC-NEW test statistic could be defined as:[116]

$$ENC - NEW = n \frac{\frac{1}{n}\sum_{t=T+1}^{T+n} e_{it}\left(e_{it} - e_{jt}\right)}{\frac{1}{n}\sum_{t=T+1}^{T+n} e_{jt}^{2}}. \tag{3.7.7}$$

Clark and McCracken employed numerical methods, founded upon five thousand independent draws, to produce asymptotic critical values for the three different tests. Reliance was then placed upon the asymptotic critical values for establishing the finite-sample properties of the tests. However, the ENC-T and ENC-REG tests were also conducted utilising critical values according with a standard normal distribution.

On the basis of Monte Carlo simulations involving the asymptotic critical values, the ENC-NEW and ENC-REG tests were seen to be subject to only slight size distortions. Also, the ENC-T test was observed to perform reasonably well; the empirical size deviated to the greatest extent from the nominal size of 0.10 when the number of forecasts was small. In contrast, when the ENC-T and ENC-REG tests utilised critical values which were associated with the standard normal distribution, there generally occurred too infrequent rejections of the null hypothesis. Also, the problem of an undersized test became more severe as n was allowed to increase.

Simulations were also undertaken in order to calculate the size-adjusted powers of the three tests under different circumstances. On the basis of the results which were

[116] This equation corresponds to equation (3) on p. 93 of the article by Clark and McCracken (2001), and is consistent with one-step-ahead forecasts being generated.

obtained by Clark and McCracken, the ENC-NEW test had to be ranked above the other two tests, which were of an approximately equal standing. It was also observed that, with the value of n fixed, power tended to rise with an increase in the number of observations which were initially used in estimation (and *vice versa*).[117]

A feature of the studies which have been discussed so far in this section is the assumption that values of the population parameters which reside in regression models that form the basis for prediction are known with certainty. However, West (2001) sought to examine the consequences for the properties of a test for forecast encompassing of the values of the population parameters requiring estimation.

The general implication of ignoring uncertainty is too frequent rejection of the null hypothesis. In order to establish the severity of this problem, though, West elected to perform Monte Carlo experiments. Ten thousand replications were conducted, with errors being drawn from a normal distribution. Two-sided tests of forecast encompassing were performed at the five per cent level of significance.

The properties of a test which bore a close resemblance to that which had been proposed by Harvey *et al*. (1998)[118] were contrasted with those of a test which made an allowance for parameter uncertainty. West reported the empirical sizes of the tests for different combinations of n and n/T. From an observation of the relevant table, it was possible to conclude that the test which abstracted from accounting for sampling

[117] The study by Clark and McCracken (2001) also included an empirical application which featured the two variables, the rate of consumer price inflation and the male unemployment rate. From the analysis which was performed, it seemed that tests of forecast encompassing enjoyed a power advantage over tests of equal forecast accuracy.

[118] More specifically, a degrees-of-freedom adjustment was applied to the statistic which was favoured by Harvey *et al*. (1998).

error in estimation was most accurate in the environment of a small number of forecasts (in absolute and proportional terms). In contrast, for the test which explicitly catered for sampling error, the empirical size was generally close to the nominal size of 0.05.

Harvey and Newbold (2005) also examined the implications for forecast encompassing of uncertainty surrounding values of population parameters. More specifically, reference was made to the two frameworks for testing which have been presented earlier in this section. Recall the unconstrained equation which was attributed to Fair and Shiller (1990):

$$y_t = a + b_1 y^*_{it} + b_2 y^*_{jt} + \varepsilon_t. \tag{3.7.2}$$

Recollect that, when the restriction was imposed that individual forecasts are unbiased, the above equation became:

$$e_{it} = b_2(e_{it} - e_{jt}) + \varepsilon_t. \tag{3.7.6}$$

On the basis that model i (which generates the forecasts, y^*_{it} (t = T+1, T+2, ..., T+n)) represents the data-generating process then, with respect to both of the above models, b_2 should be equal to zero. However, the necessity to estimate the values of the population parameters in the rival models, i and j, may serve to prevent y^*_{it} from encompassing y^*_{jt}. Additionally, though, the requirement to estimate the values of the parameters, a, b_1 and b_2, in the above equations, may result in a linear combination of the forecasts which are produced by the estimated versions of the true and misspecified models being of no greater accuracy than a prediction which is delivered by, alone, the estimated form of the data-generating process.

Harvey and Newbold initially conducted analysis in the environment of two bivariate, non-nested models, which were estimated using OLS. The sample regression equations were then employed to generate one-step-ahead forecasts. The extent to which b_2 differed from zero, in both constrained and unconstrained contexts, was determined by Monte Carlo experiments. Following one hundred thousand replications, it was discovered that, in the presence of small samples, the optimal value of b_2 possessed the capability of being substantially different from zero. Factors which governed the extent of the departure from zero included: the size of the slope parameter in the data-generating process; and the signal-to-noise ratio for the true model.[119]

Harvey and Newbold proceeded to obtain one-step-ahead predictions from the competing models through application of rolling regressions. The forecasts were subsequently used in conjunction with the constrained and unconstrained models, above, for the purpose of estimating the parameters, a, b_1 and b_2. Having undertaken simulations, it was observed that improvements in forecast accuracy were attainable by combining forecasts, in the case of large n, paired with small T. However, where the size of T prohibited n from being large, the most accurate forecasts were seen to be derived from the true model.

[119] More specifically, the deviation was found to be smaller, the larger was the size of the slope parameter and the greater was the signal-to-noise ratio.

Harvey and Newbold also assumed that the two rival models were first-order autoregressive and moving average processes. From an initial simulation analysis, where optimal values were assigned to the parameters, a, b_1 and b_2, it was possible to reach the conclusion that the inability of forecasts generated by a true model to encompass those which emanated from a misspecified model was more apparent for predictions corresponding to dynamic processes than those which were founded upon static models. When allowance was made, though, for the values of the aforementioned parameters to be estimated then the gains in forecast accuracy which were accrued by combining the forecasts from the competing models were limited to relatively large values of n.

A final example which was used by Harvey and Newbold involved bivariate models where predictions were required of the values of the regressors. The extra uncertainty which was introduced into the analysis resulted in the optimal values of b_2 generally being further away from zero. Thus, it was possible to conclude that the failure to achieve the property of encompassing is more distinct when future values of right-hand-side variables are unknown. However, in the context of the parameters in the constrained and unconstrained models necessitating estimation, simulation results indicated that, for a given value of T, a large value of n would be required for a linear combination of forecasts to be associated with a greater degree of accuracy than predictions that were produced by the estimated form of the data-generating process.

3.8 Summary

The aim of this chapter has been to explain a methodology which is considered to be suitable for the purpose of investigating the relationship between the price of oil and U.K. macroeconomic performance. Upon embarking upon an empirical investigation, it is necessary to take several key decisions. A fundamental choice is the framework that is to be used for analysis. In section 3.1, a preference was exhibited for limiting the role that is played by economic theory and so to place reliance upon an unrestricted VAR model. The variables that enter this system should correspond to the description of an open economy. In order to facilitate a comparison of results, the variables which are to be included in the model are identical to those which featured in the comprehensive study by Jimenez-Rodriguez and Sanchez (2005).

Quarterly time series are available on all of the variables that have been recommended for admission to the VAR system. Given the reluctance to model macroeconomic behaviour prior to the introduction of a floating exchange rate regime in the early 1970s, there appeared to be no advantage to be gained from undertaking estimation in conjunction with data of an annual frequency.

Extensive discussion occurred concerning whether or not it was preferable to operate with seasonally-adjusted data on the relevant variables. While it was respected that an analysis of data of this type could give rise to certain statistical distortions, this negative aspect was outweighed by the opportunity to construct more concise models and the ability to perform more straightforward comparisons with the findings from related studies.

Mention was given to the possibility of achieving spurious results being diminished by incorporating variables in a VAR model in a form such that the associated time series are stationary. For the purpose of establishing the statistical properties of a time series, it is possible to conduct unit root tests. The most popularly applied procedure within the empirical literature would seem to be the ADF test. However, the latter has been subject to criticism for its lack of power. Consequently, it was decided to adopt additionally an approach that has been demonstrated to be statistically superior and which seeks to eliminate the deterministic elements from a time series by means of Generalised Least Squares estimation, i.e., the DF-GLS test of Elliott *et al*. (1996).

It was recognised that the standard form of a VAR model could be efficiently estimated using Ordinary Least Squares, on the basis that exactly the same regressors feature on the right-hand side of every one of the constituent equations. Having estimated a VAR model, established practices consist of performing Granger-causality tests, generating impulse responses, and undertaking forecast error variance decompositions. The latter two activities are founded upon the moving average representation of the VAR model, involving orthogonalised innovations. For the purpose of achieving the latter, a Cholesky decomposition was favoured as this would minimise the contribution that was made by economic theory. Out of a desire to maximise objectivity, the endogenous variables would be presented in the order that had been employed in the study by Jimenez-Rodriguez and Sanchez (2005).

It was appreciated that, for the purpose of assessing the validity of a single specification or choosing between rival models, a post-sample analysis could prove beneficial. An observation of the signs and magnitudes of forecast errors would provide an indication of the adequacy of the corresponding equation. Also, formal tests have been proposed by Diebold and Mariano (1995) and Harvey *et al*. (1997) which enable an evaluation of whether or not alternative models are associated with the same degree of forecast accuracy.

The concept of forecast encompassing was discussed in the later part of section 3.7. A consideration of the literature on this topic provided encouragement to apply the test that was proposed by Harvey *et al*. (1998). However, on the basis of its superior statistical properties, which were demonstrated by Clark and McCracken (2001), the ENC-NEW test would also be conducted in suitable situations.

CHAPTER FOUR

EMPIRICAL ANALYSIS PERFORMED IN CONJUNCTION WITH UNRESTRICTED VAR MODELS

4.1 Definitions of Variables, Data Sources and Statistical Properties of Time Series

Within the preceding chapter of this thesis, a justification was provided for choosing variables to enter the empirical analysis that are in accordance with those which featured in the study by Jimenez-Rodriguez and Sanchez (2005). As a reminder, these variables consisted of real G.D.P., the real effective exchange rate, the real price of oil, the real wage, price inflation, a short-term rate of interest, and a long-term rate of interest. A preference has been exhibited for collecting data which are of a quarterly frequency. Prior to creating lags or undertaking transformations, the sample period extends from 1972q1 to 2008q1.[120] At the beginning of this empirical section, for each of the variables, in turn, a formal definition is supplied and the source of the data is indicated. The time series is then presented in the form of a line graph, on the basis of which some fundamental observations are made. Results of unit root tests are subsequently reported which serve to aid the decision on the order of integration and thus the manner in which the variable should be contained within the VAR model.

It should be respected that an element of discretion will be permitted in terms of interpreting the results of the unit root tests, on the basis that, on occasions, the strict

[120] The equations of a model are estimated using data which extend to 2005q1. The post-sample performance is examined over the interval, 2005q2-2008q1.

application of a unit root test can be observed to deliver a perverse outcome. Also, the decision concerning the order of integration of a variable should be mindful of the findings of earlier studies using similar data. As has been mentioned, the study by Jimenez-Rodriguez and Sanchez (2005) is regarded as a suitable influence on the choice of variables entering the analysis. Hence, it seems to be appropriate to give consideration especially to the conclusions of their preliminary investigation of the stochastic properties of the seven quarterly time series. On page 208 of their article, Jimenez-Rodriguez and Sanchez report that the results which are obtained from the implementation of formal unit root tests are that all of the seven variables are integrated of order one. Consequently, the approach which is adopted in this section of the thesis is to operate according to the premise that each variable is integrated of order one, only seeking to revise this judgement if there is convincing evidence in contradiction of this hypothesis.

4.1.1 Gross Domestic Product (GDP)

Formal definition: U.K. Gross Domestic Product, chained volume measure, seasonally adjusted, constant (2002) prices.

Data source:

www.statistics.gov.uk/statbase/TSDdownload2.asp (*Economic Trends Annual Supplement*, Table 1.2 (ABMI)), accessed July 2006.[121]

[121] This source specifically provided quarterly data from 1972q1 to 2005q1. For the purpose of conducting a post-sample analysis, the series was subsequently extended through accessing the Office for National Statistics website on 25th May 2010. On account of the more recent data being expressed in terms of 2005 prices, it was necessary to perform a splicing operation in order to obtain a consistent time series.

Figure 4.1.1.1: U.K. Gross Domestic Product

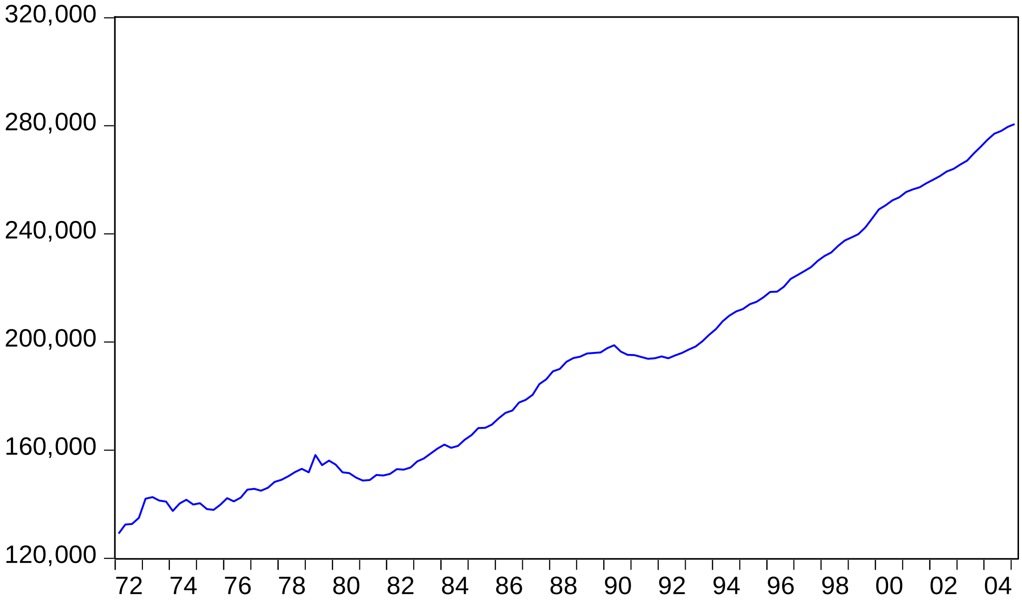


Figure 4.1.1.1 shows the behaviour of U.K. GDP over the interval, 1972q1–2005q1. Upon observing the graph, it is apparent that the tendency has been for GDP to increase over the period. Indeed, the average annualised quarterly percentage change in GDP is calculated to be equal to 2.38.[122]

In addition to containing a trend, the graph exhibits a cyclical pattern. The periods over which the U.K. has been subject to an economic recession are identified as being: 1973q3–1974q1 (corresponding to a 3.55 per cent fall in GDP); 1975q2 – 1975q3 (1.75 per cent); 1980q1 – 1981q1 (4.74 per cent); 1990q3 – 1991q3 (2.52 per cent).[123] However, from 1991q4 to 2005q1, the U.K. enjoyed fifty-four consecutive quarters of positive growth of GDP. Indeed, over this interval, the average annualised quarterly percentage change in GDP equalled 2.76.

[122] For clarification, the annualised quarterly percentage change in the variable, X, is calculated using the formula $400*(X_t - X_{t-1})/X_{t-1}$.
[123] A recession is defined as at least two consecutive quarters of negative growth of GDP.

Both the ADF and the DF-GLS unit root tests are applied to the series on the natural logarithm of GDP.[124] When performing these tests, the maximum number of lags on the dependent variable within the test equation is determined by the Schwert (1989) formula, while the optimal number is selected in accordance with the MAIC, which was favoured by Ng and Perron (2001). The results of the unit root tests are shown in Table 4.1.1.1, below.

Table 4.1.1.1: Results of Unit Root Tests Applied to log.(GDP)

Unit Root Test		Deterministic Terms Allowed For In The Procedure	
		Intercept/No Trend	Intercept and Trend
ADF test			
Computed value of statistic		0.5028	-2.5866
number of lags		3	3
probability value		0.9863	0.2872
DF-GLS test			
Computed value of statistic		3.2439	-2.5276
number of lags		4	3
10% critical value		-1.6151	-2.7110

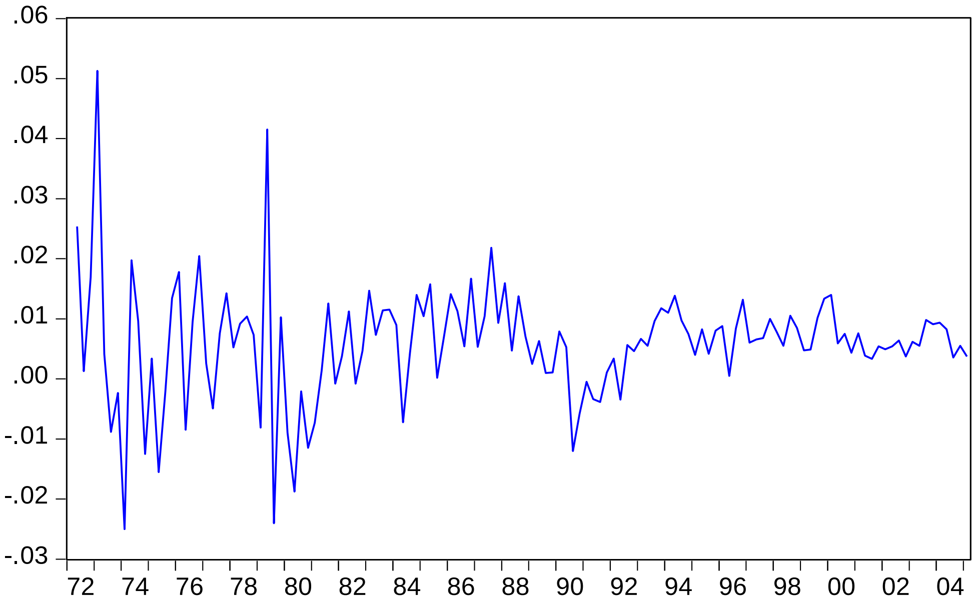
The information which is contained in the table, above, indicates that, irrespective of the type of test or the context within which the test is conducted, at a conventional level of significance, it is not possible to reject the null hypothesis which asserts that

[124] The convention in the econometric modelling of time-series data is to contain variables in the form of a logarithm, unless the variable is expressed as a rate, such as unemployment or a Treasury bill yield.

the process which is responsible for the series on the logarithm of GDP includes a unit root.[125]

Accordingly, unit root tests are now performed in conjunction with the series on the first-difference of the logarithm of GDP. The line graph of the time series is displayed below (Figure 4.1.1.2), following which, within Table 4.1.1.2, there can be found the results of the ADF and DF-GLS tests.

Figure 4.1.1.2: First-Difference of the Logarithm of GDP



[125] In all four cases, the adoption of a sequential testing procedure delivers an optimal lag length of eight quarters. However, at a conventional level of significance, it is still not possible to reject the null hypothesis of a unit root. With respect to subsequent unit root tests, the consequence of the implementation of this alternative selection method will only be mentioned if this conflicts with the inference concerning the presence of a unit root that is drawn from the use of the MAIC.

Table 4.1.1.2: Results of Unit Root Tests Applied to Δlog.(GDP)

Unit Root Test		Deterministic Terms Allowed For In The Procedure
		Intercept/No Trend
ADF test		
Computed value of statistic		-5.8481
number of lags		3
probability value		0.0000
DF-GLS test		
Computed value of statistic		-1.4620
number of lags		3
10% critical value		-1.6151

Upon observing the contents of the table, above, it is apparent that the two test procedures provide conflicting evidence. Only when performing the ADF test is the inference drawn that the series on Δlog.(GDP) is stationary. The same discrepancy can be observed within the paper by Jimenez-Rodriguez and Sanchez (2005, Table 1A, p. 204). Without discussion, they proceeded to interpret the logarithm of GDP as being integrated of order one. In order to facilitate a comparison of the results which are produced in this chapter of the thesis with those which were generated by Jimenez-Rodriguez and Sanchez, there is encouragement to proceed, ignoring the outcome of the DF-GLS test. However, it is possible that the latter is reflecting what is clearly a non-constant variance of the quarterly growth of GDP.[126] As

[126] From the sub-period, 1972q1 – 1981q4, to the sub-period, 1982q1 – 2005q1, there occurs a fall in the standard deviation from 0.0158 to 0.0053.

corroborating evidence, when the DF-GLS test is performed in conjunction with the series on the first-difference of the logarithm of GDP, using data from only 1982q1 to 2005q1, the computed value of the test statistic is –2.3785, which is considerably less than the corresponding five per cent critical value of –1.9443. Hence, although the decision will be taken to follow the practice of Jimenez and Rodriguez, there would seem to be an incentive, in order to check on the robustness of the results which are obtained from estimation of the VAR systems, also to conduct analysis over a more restricted sample period, commencing in 1982q1.[127]

4.1.2 Real Effective Exchange Rate (REER)

Formal definition: Great Britain, real effective exchange rate (founded on consumer price indices), expressed in the form of an index such that, in 2000, the value of the variable is equal to 100.

Data source:

O.E.C.D. Main Economic Indicators (GBR.CCRETT01.IXOB), accessed July 2006.[128]

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[127] A further motivation to treat the logarithm of GDP as being integrated of order one is that the feature of a non-constant variance is not removed by applying the first-difference operator twice to the variable. Additionally, when the DF-GLS test is performed in conjunction with the series on Δ^2log.(GDP), at a conventional level of significance, it is not possible to reject the null hypothesis of a unit root.

[128] This source specifically provided quarterly data from 1972q1 to 2005q1. For the purpose of conducting a post-sample analysis, the series was subsequently extended through accessing the same database on 25th May 2010. A splicing operation was implemented in order to achieve a consistent time series.

Figure 4.1.2.1: U.K. Real Effective Exchange Rate

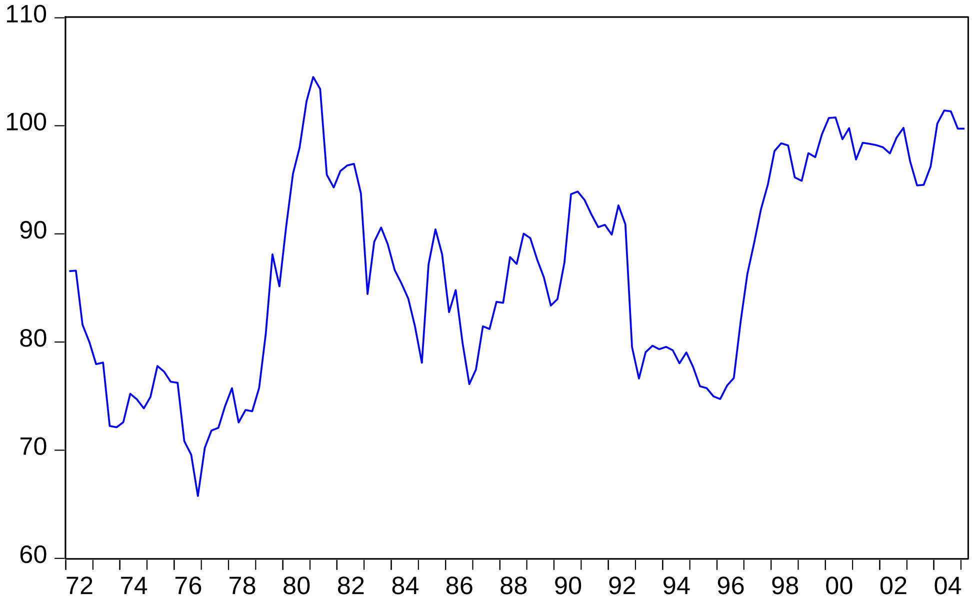


Figure 4.1.2.1 indicates the behaviour of the real effective exchange rate over the period, 1972q1–2005q1. From a study of the graph, it is evident that the exchange rate has been subject to considerable fluctuation. The value of the variable has ranged from a minimum of 65.75 (in 1976q4) to a maximum of 104.52 (in 1981q1). Over the period, as a whole, there has occurred an increase in the value of the real effective exchange rate, with the average annualised quarterly percentage change being calculated as 0.6776.

The graph reveals that there have been two periods over which the real value of sterling has appreciated sharply: from 1979q1 to 1981q1, the real effective exchange rate increased by 42.01 per cent; and from 1996q2 to 1998q2, there was witnessed a rise in the index of 31.66 per cent. Two periods which were associated with a significant depreciation in the real value of the U.K.'s currency can be identified as: 1972q1–1973q4 (over which the real effective exchange rate decreased by 16.70 per cent); and 1992q3–1993q1 (over which the index fell by 17.30 per cent).

Unit root tests are initially applied to the series on the natural logarithm of the real effective exchange rate. The results of these tests are presented in Table 4.1.2.1.

Table 4.1.2.1: Results of Unit Root Tests Applied to log.(REER)

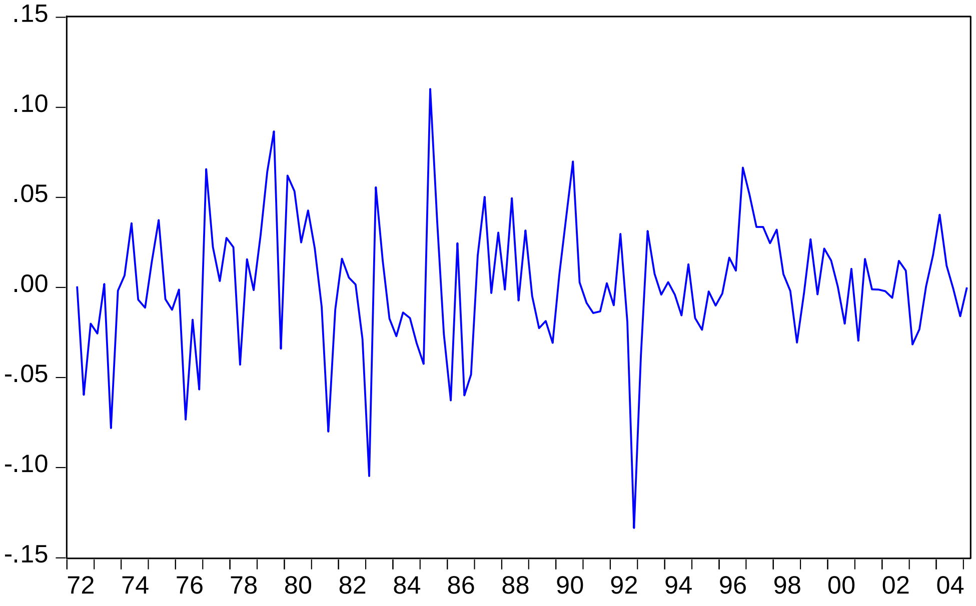
Unit Root Test		Deterministic Terms Allowed For In The Procedure	
		Intercept/No Trend	Intercept and Trend
ADF test			
Computed value of statistic		-2.0264	-2.4108
number of lags		1	0
probability value		0.2753	0.3723
DF-GLS test			
Computed value of statistic		-2.0534	-2.4731
number of lags		1	1
10% critical value		-1.6151	-2.7090

Following an inspection of Table 4.1.2.1, it is apparent that, irrespective of whether or not the test equation includes a deterministic trend term, the inference that is drawn from performing the ADF test, at a conventional level of significance, is that the time series is non-stationary. In contrast, the outcome of the DF-GLS test is seen to be sensitive to the context within which the unit root test is undertaken. When no allowance is made for a linear trend term to enter the analysis, the null hypothesis of a unit root can be rejected at the ten per cent level of significance. However, when catering for a linear trend in the time series, the computed value of the test statistic exceeds the ten per cent critical value.[129]

The evidence is therefore confused concerning whether or not the process which is responsible for the data on the logarithm of the real effective exchange rate incorporates a unit root. Note that, with respect to this variable, Jimenez-Rodriguez and Sanchez were confronted by equally contradictory results, following the application of both ADF and DF-GLS tests.[130] As has been mentioned, their decision was to err on the side of caution, electing to regard the mechanism underlying the data as accommodating a unit root.

Consequently, there is presented below, in Figure 4.1.2.2, the line graph of the series on the first-difference of the logarithm of the U.K.'s real effective exchange rate.

Figure 4.1.2.2: First-Difference of the Logarithm of REER



[129] When the sequential testing procedure is employed, the optimal choice of lag length is always the maximum twelve quarters. In three cases, at the ten per cent level of significance, the inference is drawn that there is no unit root.

[130] See Table 1A, p. 204, of the article by Jimenez-Rodriguez and Sanchez (2005).

An observation of Figure 4.1.2.2 reveals less of a tendency for the first-difference of the logarithm of the real exchange rate to wander over time than its predecessor. Also, there is no identifiable trend in the series on the first-difference of the logarithm of the real exchange rate. Hence, the ADF and DF-GLS tests are conducted without permitting a linear trend term to enter the analysis. The results which are achieved following the implementation of the two test procedures are reported in Table 4.1.2.2, below.

Table 4.1.2.2: Results of Unit Root Tests Applied to Δlog.(REER)

Unit Root Test		Deterministic Terms Allowed For In The Procedure
		Intercept/No Trend
ADF test		
Computed value of statistic		-9.3798
number of lags		0
probability value		0.0000
DF-GLS test		
Computed value of statistic		-2.4652
number of lags		12
10% critical value		-1.6149

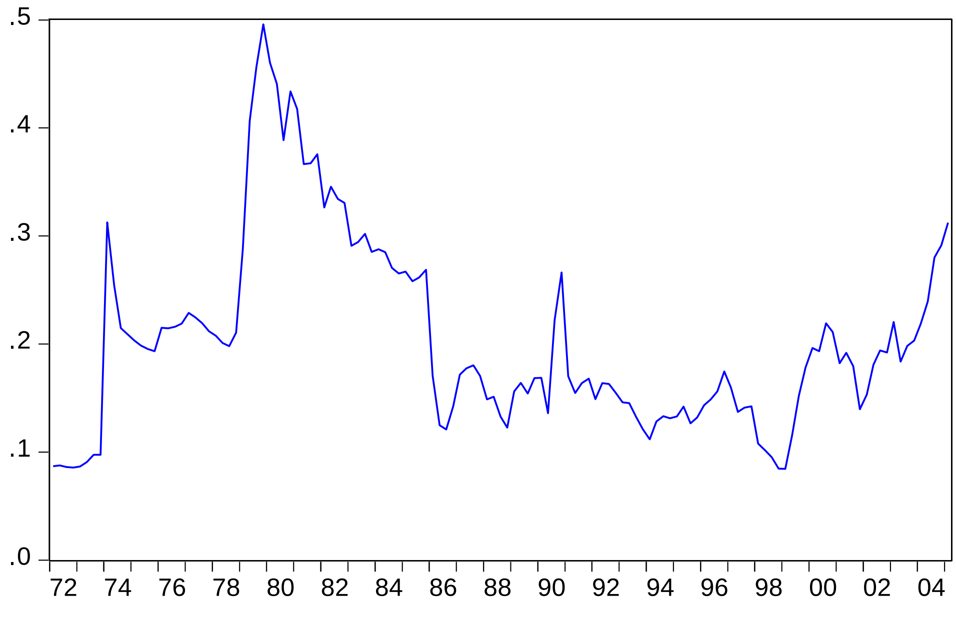
An examination of the contents of Table 4.1.2.2 indicates that, using either of the two unit root tests, the outcome is a clear rejection of the null hypothesis. Hence, the verdict which is reached from the statistical investigation is that the series on the first-difference of the logarithm of the real effective exchange rate of the U.K. is stationary. For the purpose of subsequent empirical analysis, then, the logarithm of the real effective exchange rate is treated as being integrated of order one.[131]

4.1.3 Real Price of Oil (ROILP)

Formal definition: nominal price of U.K. Brent crude oil (U.S. dollars per barrel)/U.S. Producer Price Index (seasonally adjusted, year 1982 = 100, averages of the respective monthly figures).

Data sources:
nominal price of oil - *International Financial Statistics*, Line 11276AAZZF, accessed July 2006; U.S. Producer Price Index – www.econmagic.com/em-cgi/data.exe/feddal/wsop03sa (Dallas FRB), accessed July 2006.[132]

Figure 4.1.3.1: Real Price of Brent Crude Oil



[131] The DF-GLS test was also performed imposing a number of lags on the dependent variable in the test equation which matched the number which was deemed to be optimal when conducting the corresponding ADF test. In the presence of zero lags, the computed value of the test statistic equalled –9.4152, which contrasted with a ten per cent critical value of -1.6151.

[132] These sources specifically provided quarterly data from 1972q1 to 2005q1. For the purpose of conducting a post-sample analysis, both of the series were subsequently extended through accessing the same databases on 25th May 2010. With respect to the U.S. Producer Price Index, a splicing operation was implemented in order to achieve a consistent time series.

The line graph in Figure 4.1.3.1 shows the behaviour of the real price of oil from 1972q1 to 2005q1. From observing the graph, it is apparent that, over the sample period, the series contains no clear upward or downward trend. However, it is evident that the real price of oil has been subject to considerable fluctuation. The value of the variable ranges from a minimum of 0.0844 (1999q1) to a maximum of 0.4959 (1979q4). Sharp rises occurred between 1973q4 and 1974q1 (220.87 per cent), 1978q3 and 1979q4 (150.43 per cent), and 1990q2 and 1990q4 (96.08 per cent). Following the low point in 1999q1, it can be seen that the real price of oil recovered considerably until the end of the sample period (an increase of 270.17 per cent).

Regarding decreases in the real price of oil, the sharpest fall corresponds to 1986. More specifically, between 1985q4 and 1986q3, the real price of oil declined by 54.99 per cent. Also, from inspection of Figure 4.1.3.1, there is noticeable a partial correction to the oil price rise in 1973/1974. Indeed, between 1974q1 and 1975q4, the real oil price receded by 38.14 per cent. Furthermore, following the oil price hike in 1979, there occurred a steady drift downwards in the real price of oil. More precisely, between 1979q4 and 1985q3, the percentage change amounted to -47.25. Finally, the graph indicates that the escalation in the price of oil which took place in 1990 was rapidly reversed. In particular, between 1990q4 and 1991q2, the real price dropped by 41.90 per cent.

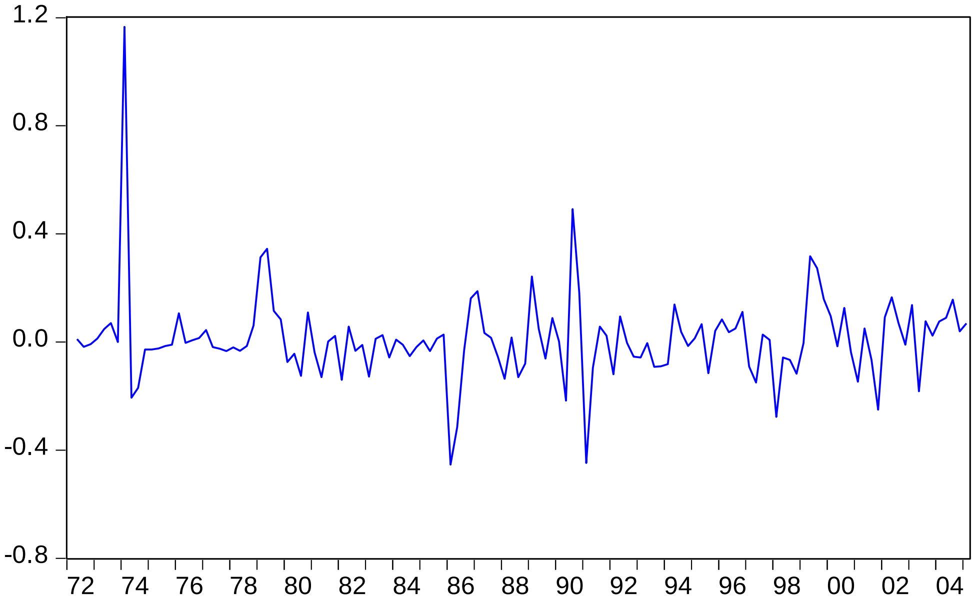
Unit root tests are performed in conjunction with the series on the natural logarithm of the real price of oil. The results which are achieved are presented in Table 4.1.3.1, below.

Table 4.1.3.1: Results of Unit Root Tests Applied to log.(ROILP)

Unit Root Test		Deterministic Terms Allowed For In The Procedure	
		Intercept/No Trend	Intercept and Trend
ADF test			
Computed value of statistic		-2.4250	-2.8252
number of lags		5	5
probability value		0.1370	0.1911
DF-GLS test			
Computed value of statistic		-0.6994	-1.4320
number of lags		5	5
10% critical value		-1.6151	-2.7130

From the application of the ADF and DF-GLS tests, at a conventional level of significance, there is agreement that the process which is responsible for generating the data on the logarithm of the real price of oil contains a unit root. Consequently, consideration is now given to the series on the first-difference of the logarithm of the real price of oil, the line graph of which is shown in Figure 4.1.3.2.

Figure 4.1.3.2: First-Difference of the Logarithm of ROILP



On the basis that, between 1972q1 and 2005q1, the quarterly growth of the real price of oil appears to fluctuate about a constant mean, the two unit root tests are conducted without allowance for a linear trend term to enter the analysis. The results of the unit root tests are shown, below, in Table 4.1.3.2.

Table 4.1.3.2: Results of Unit Root Tests Applied to Δlog.(ROILP)

Unit Root Test		Deterministic Terms Allowed For In The Procedure
		Intercept/No Trend
ADF test		
Computed value of statistic		-10.6521
number of lags		0
probability value		0.0000
DF-GLS test		
Computed value of statistic		-10.6909
number of lags		0
10% critical value		-1.6151

From an examination of the contents of the above table, it is apparent that both the ADF and the DF-GLS tests enable a rejection of, at a low level of significance, the null hypothesis of a unit root. In both cases, then, the series on the first-difference of the logarithm of the real price of oil is inferred as being stationary. The subsequent construction of VAR models is consequently founded upon the belief that the logarithm of the real price of oil is integrated of order one.

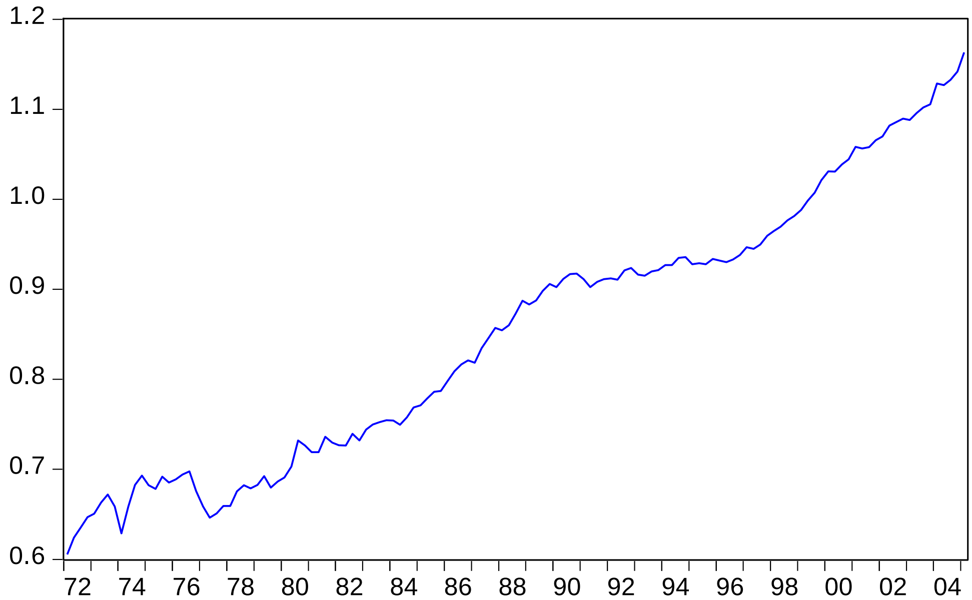
4.1.4 Real Wages (RW)

Formal definition: G.B. average earnings index (whole economy, including bonuses, seasonally adjusted, year 2000 = 100)/U.K. Consumer Price Index (CPI), where CPI = 100*U.K. household final consumption expenditure (national concept, current prices, seasonally adjusted)/U.K. household final consumption expenditure (national concept, constant (2002) prices, seasonally adjusted).[133]

Data sources:

average earnings – www.statistics.gov.uk/statbase/TSDdownload2.asp (LNMQ AEI), accessed July 2006; household final consumption expenditure (current prices) - www.statistics.gov.uk/statbase/TSDdownload2.asp (*Economic Trends Annual Supplement*, Table 1.3 (ABJQ)), accessed July 2006; household final consumption expenditure (constant prices) - www.statistics.gov.uk/statbase/TSDdownload2.asp (*Economic Trends Annual Supplement*, Table 1.3 (ABJR)), accessed July 2006.[134]

Figure 4.1.4.1: U.K. Real Average Earnings



[133] For the purpose of clarification, in this context, CPI is representing the price deflator corresponding to household consumption expenditure, rather than the official Consumer Price Index for the U.K..

[134] These sources specifically provided quarterly data from 1972q1 to 2005q1. For the purpose of conducting a post-sample analysis, all of the series were subsequently extended through accessing the Office for National Statistics website on 25th May 2010. With respect to the average earnings index and the consumer price index, splicing operations were performed in order to achieve consistent time series.

Figure 4.1.4.1, above, indicates the movement in the real consumer wage over the period extending from 1972q1 to 2005q1. The graph shows that, over the early part of the sample period, the behaviour of the real wage was relatively volatile. In contrast, from 1977q2, the series exhibits a clear upward trend. However, the growth of the real wage appears not to have been constant over time. Over the interval, 1990q4–1996q2, there occurred only a marginal rise in the real wage, with the average annualised quarterly percentage change being calculated as 0.25. In comparison, the two periods, 1977q2–1990q4 and 1996q2–2005q1, are seen to be associated with much stronger growth. The average annualised quarterly percentage growth rates which are computed are equal to 2.44 and 2.48, respectively.[135]

Unit root tests are applied to the series on the natural logarithm of the real wage, the results of which are presented in Table 4.1.4.1.

[135] For the entire sample period, the average annualised quarterly percentage change in the real wage is equal to 2.01.

Table 4.1.4.1: Results of Unit Root Tests Applied to log.(RW)

Unit Root Test		Deterministic Terms Allowed For In The Procedure	
		Intercept/No Trend	Intercept and Trend
ADF test			
Computed value of statistic		-0.3514	-2.4510
number of lags		0	0
probability value		0.9128	0.3519
DF-GLS test			
Computed value of statistic		2.2022	-2.2811
number of lags		11	0
10% critical value		-1.6150	-2.7080

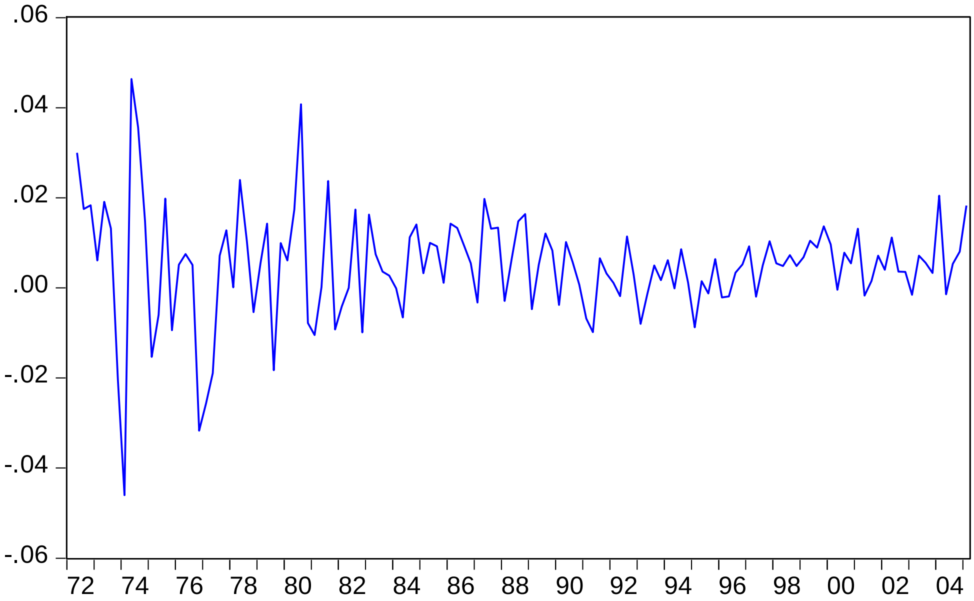
The information which is contained within the table, above, reveals that, irrespective of the type of procedure or the context within which a test is undertaken, at a conventional level of significance, the null hypothesis of a unit root cannot be rejected. Following Jimenez-Rodriguez and Sanchez (2005), the DF-GLS test is also conducted (in the presence of an intercept but not a trend term), having imposed the same number of lags on the dependent variable as were selected when performing the corresponding ADF test. However, the modification which is made to the number of lags is discovered to make no broad difference to the outcome of the test.[136,137]

[136] On the occasion when no lags are permitted on the dependent variable, the computed value of the test statistic is 3.3033, which contrasts with the corresponding ten per cent critical value of -1.6151.

[137] With reference to the DF-GLS test which is performed in the presence of a time trend, when a sequential testing procedure is relied upon, the optimal number of lags on the dependent variable is eleven quarters. In this situation, the computed value of the test statistic (-3.2254) is less than the corresponding five per cent critical value (-3.0090). Although this result enables the null hypothesis of a unit root to be rejected, the mixed nature of the statistical evidence encourages proceeding towards an inspection of the series on the first-difference of the logarithm of the real wage.

Consequently, attention is turned to the behaviour over time of the first-difference of the natural logarithm of the real wage. The associated line graph is displayed in Figure 4.1.4.2.

Figure 4.1.4.2: First-Difference of the Logarithm of RW



On the basis that the time series does not incorporate a visible trend, the ADF and DF-GLS tests are undertaken with allowance for an intercept, but not a trend term, to enter the respective model. The results which emerge from the application of the two tests are contained in Table 4.1.4.2.

Table 4.1.4.2: Results of Unit Root Tests Applied to Δlog.(RW)

Unit Root Test		Deterministic Terms Allowed For In The Procedure
		Intercept/No Trend
ADF test		
Computed value of statistic		-2.9163
number of lags		8
probability value		0.0463
DF-GLS test		
Computed value of statistic		-0.4594
number of lags		10
10% critical value		-1.6150

A study of Table 4.1.4.2 reveals a conflict between the outcomes of the two tests. In the case of the ADF test, the computed value of the associated statistic compels a rejection of the null hypothesis at the five or ten per cent level of significance. However, in connection with the DF-GLS test, the computed value of the statistic exceeds the corresponding ten per cent critical value.[138]

Similar to earlier, when considering the behaviour of the quarterly growth of GDP, there is the possibility that the result of the DF-GLS test is reflecting the non-constant variance which is evident when viewing the series on the first-difference of the logarithm of the real wage. Consequently, the same approach as before is adopted

[138] The DF-GLS test is also performed having admitted eight lags on the dependent variable to the test equation. In this situation, the computed value of the statistic is -0.6173, which is still well above the ten per cent critical value of -1.6150.

of repeating the application of the test employing a reduced sample period of 1982q1–2005q1. In this instance, the computed value of the test statistic (-1.9422) lies close to the corresponding five per cent critical value (-1.9443) and well to the left of the relevant ten per cent critical value (-1.6145).

On the basis of the accumulated statistical evidence, then, for the purpose of the later estimation of VAR models, the logarithm of the real wage variable will be regarded as having an order of integration that is equal to one. However, repeating the pronouncement which was made following the analysis of the quarterly data on U.K. GDP, it seems advisable, as a form of check on the robustness of the results which are achieved, also to conduct the subsequent empirical investigation over the shorter interval, ranging from 1982q1 to 2005q1.[139]

4.1.5 Price Inflation (PINF)

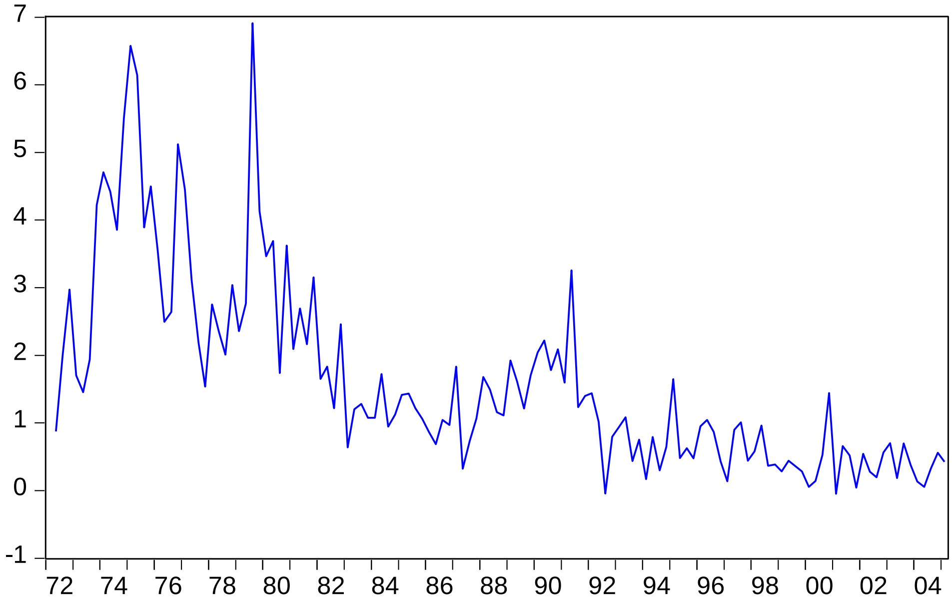
Formal definition: the quarterly percentage rate of change in the Consumer Price Index (CPI), where CPI = 100*U.K. household final consumption expenditure (national concept, current prices, seasonally adjusted)/U.K. household final consumption expenditure (national concept, constant (2002) prices, seasonally adjusted).

Data sources:

See sub-section 4.1.4.

[139] As was the case with log.(GDP), no advantage is evident by applying the first-difference operator twice to log.(RW). When performing the DF-GLS test in conjunction with the series on Δ^2log.(RW), once again, at a conventional level of significance, it is not possible to reject the null hypothesis.

Figure 4.1.5.1: U.K. Consumer Price Inflation



The line graph of the quarterly time series on consumer price inflation is shown in Figure 4.1.5.1, above. An observation of the graph reveals that there has occurred a considerable variation in the quarterly rate of price inflation over the period of interest. More specifically, the value of the variable is seen to range from a minimum of -0.05 (2001q1) to a maximum of 6.91 (1979q3). Also, it is noticeable that, over the sample interval, there were only two instances of a fall in the value of the CPI.

On the basis of Figure 4.1.5.1, there appear to be three distinct phases to the behaviour of consumer price inflation. Over the early part of the sample period, to 1982q4, the quarterly rate of price inflation was relatively high, with the average being calculated as 3.16. Also, a feature of the graph is the volatile nature of price inflation over this interval. Between 1983q1 and 1992q1, the quarterly percentage change in the CPI tended to be more modest, with the average rate falling to 1.37. Finally, towards the end of the data period, from 1992q2 to 2005q1, the rate of price inflation can be seen to be relatively low, with the average being recorded as 0.54 per cent. In addition, regarding this segment of the graph, there is observed to be very little variation about the arithmetic mean.

Unit root tests are performed in conjunction with the series on consumer price inflation. The results which are generated are disclosed in Table 4.1.5.1.

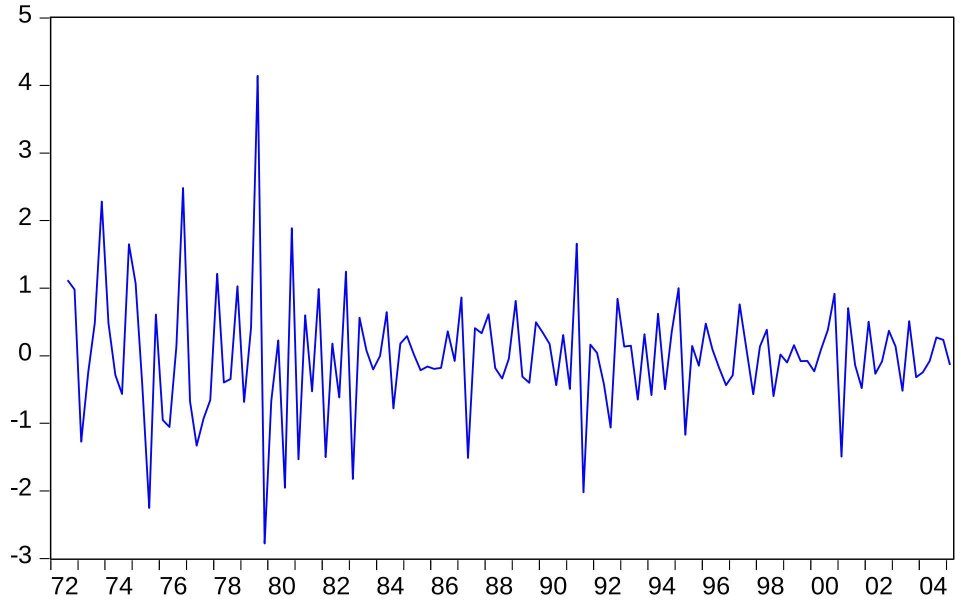
Table 4.1.5.1: Results of Unit Root Tests Applied to PINF

Unit Root Test		Deterministic Terms Allowed For In The Procedure	
		Intercept/No Trend	Intercept and Trend
ADF test			
Computed value of statistic		-1.8730	-3.1078
number of lags		10	7
probability value		0.3440	0.1091
DF-GLS test			
Computed value of statistic		-1.9040	-2.0605
number of lags		7	7
10% critical value		-1.6150	-2.7160

The figures which are contained in the above table correspond to four different unit root tests. In three cases, choosing ten per cent as the level of significance, it is not possible to reject the null hypothesis. However, when the DF-GLS test is conducted with allowance for an intercept but not a linear trend term in the respective equation, the computed value of the statistic is less than the corresponding critical value. Any suggestion that the time series on the quarterly rate of price inflation is stationary, though, is contradicted by the form of the line graph in Figure 4.1.5.1. As was indicated in the earlier commentary, there have occurred shifts over time in the mean value of the quarterly percentage rate of consumer price inflation.[140]

Hence, the analysis proceeds by applying the first-difference operator to the original variable, thereby creating the quarterly change in the rate of price inflation. The line graph of the resultant series is displayed in Figure 4.1.5.2.

Figure 4.1.5.2: First-Difference of PINF



Upon observing Figure 4.1.5.2, the mean of the respective variable does not seem to be changing in a systematic way over time. Hence, for the purpose of undertaking the ADF and DF-GLS tests, the associated models are permitted to include an intercept but not a deterministic trend term. The results which are obtained from the application of the two unit root tests are shown in Table 4.1.5.2, below.

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[140] Adopting the sequential testing procedure for determining the optimal number of lags, selecting the ten per cent level of significance, the null hypothesis is rejected in an additional situation, namely, when an ADF test is performed in the context of an equation which incorporates both an intercept and a linear trend term.

Table 4.1.5.2: Results of Unit Root Tests Applied to ΔPINF

Unit Root Test		Deterministic Terms Allowed For In The Procedure
		Intercept/No Trend
ADF test		
Computed value of statistic		-15.9017
number of lags		0
probability value		0.0000
DF-GLS test		
Computed value of statistic		-0.1212
number of lags		12
10% critical value		-1.6149

From studying the contents of Table 4.1.5.2, it is apparent that, following the implementation of the two different test procedures, dramatically different results are produced. At a conventional level of significance, the null hypothesis of a unit root is decisively rejected in the case of the ADF test. In contrast, the computed value of the statistic is well above the corresponding ten per cent critical value when performing the DF-GLS test. Again, there is the possibility that the difficulty in rejecting the null hypothesis when relying upon the DF-GLS test stems from the variance of the variable not being constant over time. From 1972q3 to 1981q4, the standard deviation of the first-difference of the quarterly percentage rate of consumer price inflation is calculated as 1.3871. Conversely, the value of the statistic for the period, 1982q1–2005q1, is only 0.6185. However, when the DF-GLS test is undertaken over merely the latter sub-period, the verdict is, once again, that the relevant series is non-stationary.[141] On this occasion, the explanation for the outcome of the DF-GLS test seems to be the number of lags on the dependent variable which are included within the test equation. When the number of lags is constrained to be zero (i.e., the same number as for the corresponding ADF test), the computed value of the statistic pertaining to the full (reduced) sample period is -8.9012 (-7.5840), which is much less than even the one per cent critical value of -2.5829 (-2.5901). Thus, although the accumulated evidence suffers from being ambiguous, on balance, it would seem to support proceeding to construct and estimate VAR models on the basis that the quarterly rate of price inflation is integrated of order one.

4.1.6 Short-Term Rate of Interest (TB)

Formal definition: U.K. Treasury bills, three-month yield, expressed as a percentage.

Data source: www.statistics.gov.uk/statbase/TSDdownload2.asp (*Economic Trends Annual Supplement*, Table 5.9 (AJRP)), accessed July 2006.[142,143]

The line graph of the series on the short-term rate of interest is presented in Figure 4.1.6.1, below.

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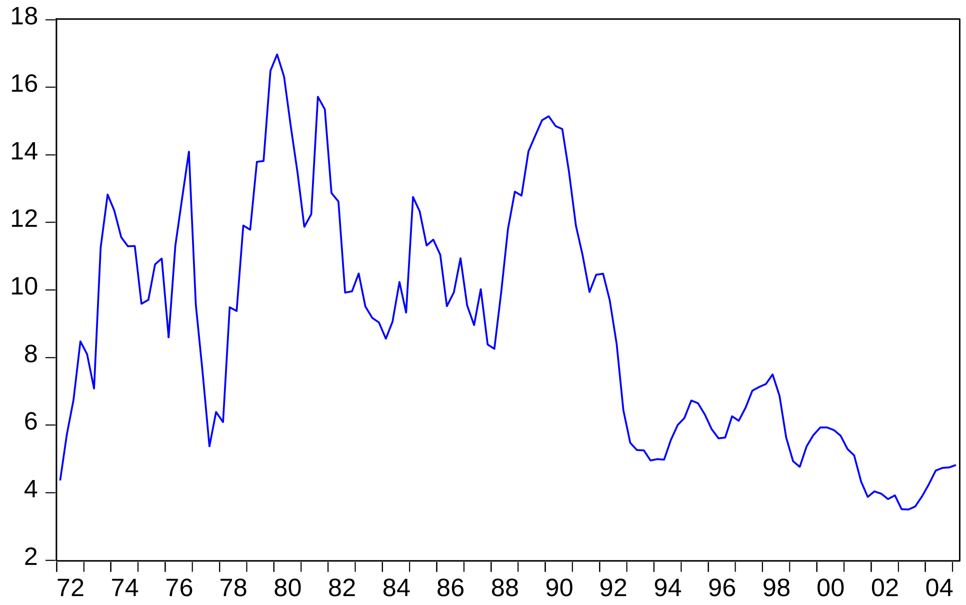
[141] The computed value of the test statistic is 0.1732, which compares with a corresponding ten per cent critical value of -1.6145 (8 lags).

[142] For 1989q3, the published figure for the Treasury bill yield was equal to zero. Hence, for the purpose of the ensuing statistical analysis, the allocated value was derived from a calculation of the average of the percentages for the two adjacent quarters, 1989q2 and 1989q4.

[143] This source specifically provided quarterly data from 1972q1 to 2005q1. For the purpose of conducting a post-sample analysis, the series was subsequently extended through accessing the Office for National Statistics website on 7th June 2010.

Figure 4.1.6.1: U.K. Treasury Bill Yield



An inspection of the graph reveals that, over the time period, 1972q1–2005q1, the value of the short-term rate of interest has fluctuated considerably, although seemingly not about a constant mean. The minimum value of the variable is 3.50 per cent (2003q2), while the highest value that is recorded is 16.97 per cent (1980q1). A downward step is visible in the graph *circa* 1993. From 1972q1 to 1993q1, the mean value of the interest rate is calculated as 10.89 per cent. In contrast, between 1993q2 and the end of the sample period, 2005q1, the arithmetic average is computed to be 5.34 per cent.

The series thus has the appearance of being non-stationary. The ADF and DF-GLS tests are now performed in order to determine whether or not such an impression is confirmed. The results of the unit root tests are displayed in Table 4.1.6.1.

Table 4.1.6.1: Results of Unit Root Tests Applied to TB

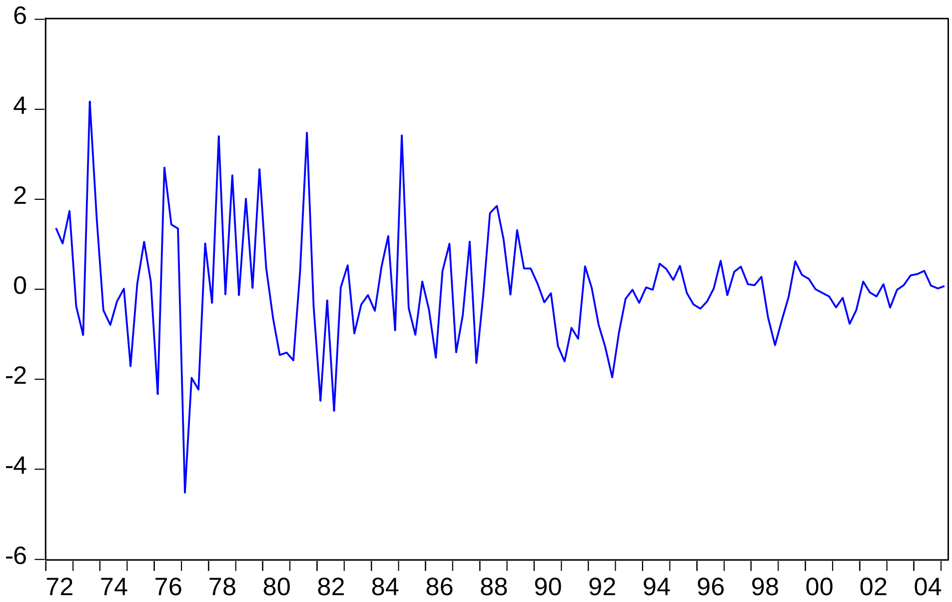
Unit Root Test		Deterministic Terms Allowed For In The Procedure	
		Intercept/No Trend	Intercept and Trend
ADF test			
Computed value of statistic		-1.1379	-3.4781
number of lags		10	0
probability value		0.6992	0.0460
DF-GLS test			
Computed value of statistic		-1.6713	-1.1973
number of lags		6	10
10% critical value		-1.6150	-2.7180

The results which are obtained from the different unit root tests which are conducted send mixed signals. Adopting a framework which does not admit a deterministic trend term, choosing the ten per cent level of significance, in performing an ADF test, the null hypothesis of a unit root cannot be rejected. In contrast, the inference which is drawn from applying the DF-GLS test is that the series on TB is stationary. However, when the model is extended to include a linear trend term, as well as an intercept parameter, there occurs a reversal of outcomes. More specifically, on the basis of the ADF test, it is now possible to reject the null hypothesis at the ten (and five) per cent level of significance.[144] With reference to the DF-GLS test, though, the computed value of the statistic lies well above the corresponding ten per cent critical value.

[144] In this context, the implementation of a sequential testing procedure for determining the optimal number of lags yields a different outcome. The favoured number of lags is six, giving rise to a probability value for the ADF test of 0.1319.

The evidence is regarded as being insufficiently strong to be able to dismiss the notion that the data-generating process includes a unit root. Thus, the analysis proceeds by examining the series on the first-difference of the Treasury bill yield. The time plot of the variable is exhibited in Figure 4.1.6.2.

Figure 4.1.6.2: First-Difference of TB



The appearance of the graph suggests that the variable possesses a constant mean, even though its behaviour seems to be far more erratic over the first half of the sample period. On this occasion, then, the ADF and DF-GLS tests are conducted in the presence of only an intercept and not a trend term. The results which are achieved are shown in Table 4.1.6.2.

Table 4.1.6.2: Results of Unit Root Tests Applied to ΔTB

Unit Root Test		Deterministic Terms Allowed For In The Procedure
		Intercept/No Trend
ADF test		
Computed value of statistic		-7.3345
number of lags		1
probability value		0.0000
DF-GLS test		
Computed value of statistic		-1.0389
number of lags		11
10% critical value		-1.6151

Once again, following the application of different unit root tests, the results which are obtained are seemingly contradictory. From the implementation of the ADF test procedure, using a conventional level of significance, there occurs a decisive rejection of the null hypothesis of a unit root. In contrast, the computed value of the DF-GLS statistic lies well to the right of the corresponding ten per cent critical value. However, with respect to the DF-GLS test, the chosen number of lags on the dependent variable in the test equation is eleven. When the latter is performed, subject to the constraint that the selected number of lags matches the number which is considered to be optimal when undertaking the comparable ADF test, the computed value of the test statistic falls to as low as –4.5827. This value is comfortably less than the corresponding ten per cent critical value of –1.6151. Consequently, although the evidence is far from clear, it seems to tilt towards the short-term rate of interest being integrated of order one. Hence, in later VAR models, the variable will be contained in a first-differenced form.[145,146]

4.1.7 Long-Term Rate of Interest (LTIR)

Formal definition: U.K. long-dated (20 years) par yield, expressed as a percentage per annum.

Data source: www.statistics.gov.uk/statbase/TSDdownload2.asp (*Economic Trends Annual Supplement*, Table 5.9 (AJLX BGS)), accessed July 2006.[147]

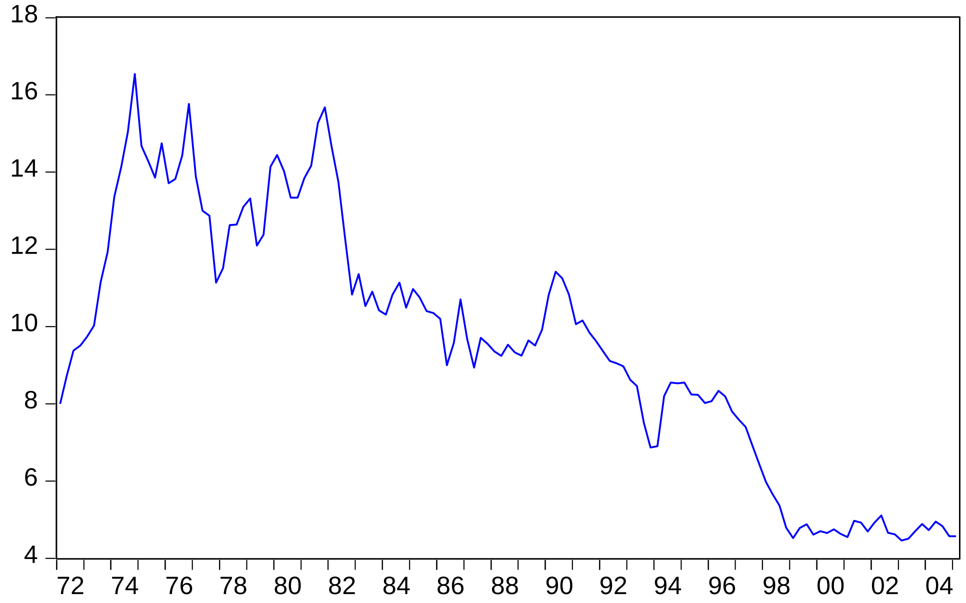
The quarterly time series on the long-term rate of interest is presented in the form of a line graph in Figure 4.1.7.1, below.

[145] Observation of Figure 4.1.6.2 also reveals a non-constant variance which is possibly contributing towards the conflicting outcomes. When the DF-GLS test is conducted over the shorter data interval, 1982q1-2005q1, the computed value of the statistic is -3.8361 (founded upon three lags on the dependent variable), which contrasts with a critical value of -2.5901, corresponding to the one per cent level of significance.

[146] Undertaking a DF-GLS test in conjunction with the time series on Δ^2TB suggested that there would be no merit in further differencing the short-term rate of interest. More specifically, in this instance, the computed value of the test statistic is -1.6048 (intercept/no trend, twelve lags), which is marginally greater than the corresponding ten per cent critical value (-1.6149).

[147] This source specifically provided quarterly data from 1972q1 to 2005q1. For the purpose of conducting a post-sample analysis, the series was subsequently extended through accessing the Office for National Statistics website on 8th June 2010.

Figure 4.1.7.1: U.K. Long-Term Rate of Interest



From observing the line graph, it can be seen that the sample period commences with eleven consecutive rises in the long-term rate of interest, culminating in a peak value of 16.54 per cent in 1974q4. Thereafter, the movement in the variable is predominantly downwards, until 1999q4, following which the value of the rate of interest appears to remain in the vicinity of 4.75 per cent.[148,149]

Unit root tests are undertaken in conjunction with the series on the long-term rate of interest, the results of which are displayed in Table 4.1.7.1, below.

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[148] It should be recognised, though, that from 1977q4 to 1981q4, the rate of interest ascended from 11.14 to 15.68 per cent.

[149] The minimum value which is recorded between 1999q4 and 2005q1 is 4.46 per cent, which corresponds to the quarter, 2003q1.

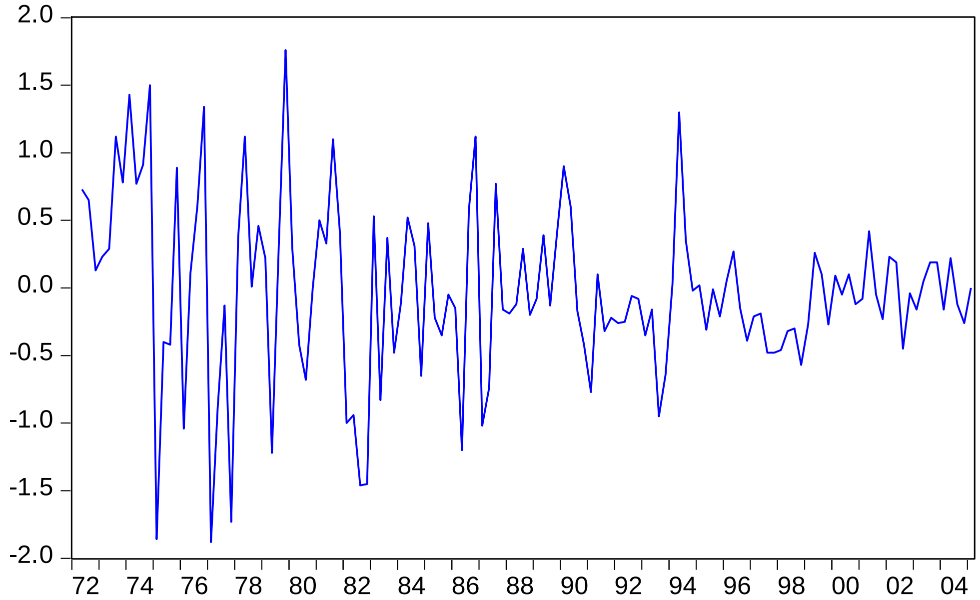
Table 4.1.7.1: Results of Unit Root Tests Applied to LTIR

Unit Root Test		Deterministic Terms Allowed For In The Procedure	
		Intercept/No Trend	Intercept and Trend
ADF test			
Computed value of statistic		-0.5691	-4.3087
number of lags		5	0
probability value		0.8723	0.0042
DF-GLS test			
Computed value of statistic		-0.9108	-1.3301
number of lags		2	2
10% critical value		-1.6151	-2.7100

Regarding the information which is contained in Table 4.1.7.1, in three out of the four cases, it is not possible to reject, at the ten per cent level of significance, the null hypothesis of a unit root. The exception is when the ADF test is performed in the context of both an intercept and a linear trend term being present in the test equation.[150] On the basis of an absence of compelling evidence to contradict the notion that the data-generating process includes a unit root, consideration is now given to the series on the first-difference of the long-term rate of interest. The line graph of the latter is shown below in Figure 4.1.7.2.

[150] When the DF-GLS test is undertaken, allowing for an intercept and a trend term to enter the analysis, but imposing the constraint that no lags on the dependent variable reside in the test equation, the computed value of the test statistic is barely disturbed (-1.3083), and so is still far in excess of the respective ten per cent critical value (-2.7080).

Figure 4.1.7.2: First-Difference of LTIR



The application of the first-difference operator to the long-term rate of interest appears to have the effect of removing the trend from the data series (even though this has failed to deliver a series which is associated with a constant variance). On this occasion, then, the ADF and DF-GLS tests are conducted in the presence of an intercept but not a linear trend term. The results which are achieved following the implementation of the two unit root tests are presented in Table 4.1.7.2.

Table 4.1.7.2: Results of Unit Root Tests Applied to ΔLTIR

Unit Root Test		Deterministic Terms Allowed For In The Procedure
		Intercept/No Trend
ADF test		
Computed value of statistic		-9.6812
number of lags		0
probability value		0.0000
DF-GLS test		
Computed value of statistic		-1.2337
number of lags		7
10% critical value		-1.6150

A study of the contents of Table 4.1.7.2 reveals that, having performed the two unit root tests, different conclusions are reached. The inference which is drawn, having conducted the ADF test, is that the series on the first-difference of the long-run rate of interest is stationary. In contrast, in the case of the DF-GLS test, the computed value of the test statistic lies to the right of the relevant ten per cent critical value. The same as when examining the data on the first-difference of the logarithm of GDP and the first-difference of the logarithm of the real wage, there is the possibility that the outcome of the DF-GLS test is a reflection of the non-constant variance which is evident in Figure 4.1.7.2. Indeed, when restricting the estimation period to 1982q1–2005q1, the computed value of the DF-GLS statistic is -1.8627, which contrasts with a ten per cent critical value of -1.6145.[151] Consequently, if the VAR model is subsequently constructed on the basis that the long-term rate of interest is integrated of order one then it would seem to be advisable, as a form of check on the robustness of the findings, to undertake estimation over not only the full sample period but also an appropriate sub-period.[152]

4.2 Specification and Estimation of a Linear VAR Model

The framework which is initially used for analysis is the standard form of VAR model (equation (3.6.2.3)):

$$x_t = A_0 + A_1 x_{t-1} + A_2 x_{t-2} + \cdots + A_p x_{t-p} + e_t. \qquad (3.6.2.3)$$

Regarding this matrix equation, x represents a (7 x 1) vector of endogenous variables. On the basis of the results of the unit root tests which were performed earlier, the endogenous variables consist of Δlog.(GDP), Δlog.(REER), Δlog.(ROILP), Δlog.(RW), ΔPINF, ΔTB and ΔLTIR. A_0 is a (7 x 1) vector of constant terms, A_i (i = 1, 2, ..., p) denotes a (7 x 7) coefficient matrix, and e_t indicates a (7 x 1) vector of random disturbance terms. The maximum length of lag on the endogenous variables, p, is intended to be sufficient for the error terms to be serially uncorrelated. However, it is accepted that, across the seven equations of the model, the stochastic terms can be contemporaneously correlated. Hence, the

[151] Still, the optimal number of lags on the dependent variable as determined by the MAIC is 7.
[152] It should also be mentioned that the inference which is drawn from the application of the DF-GLS test is sensitive to the number of lags which are included on the dependent variable in the test equation. For example, when the chosen number of lags matches the number which is considered to be optimal when performing the corresponding ADF test, the computed value of the test statistic, founded on the full data period, is –6.5924, which compares with a ten per cent critical value of –1.6151.

variance-covariance matrix belonging to e_t, which is signified by Σ, possesses an order of (7 x 7), and contains off-diagonal elements that are permitted to be non-zero.

As was mentioned in Chapter Three of this thesis, a key consideration, when specifying, a VAR system is the order (p) of the model. On the basis that none of the time series exhibit seasonal variation and out of a desire for parsimony, the maximum value of p is restricted to 4. Reliance is subsequently placed upon a sequential testing procedure, as well as different information criteria, in order to determine whether or not a smaller number of lags on the endogenous variables is acceptable.

Table 4.2.1: Values of the Modified LR Statistic and Information Criteria Corresponding to Different Orders of the Standard VAR Model

Order of VAR Model	LR Statistic	AIC	BIC	HQIC
0	N/A	-10.563	**-10.406**	**-10.500**
1	133.37	-10.912	-9.6582	-10.403
2	88.212	**-10.928**	-8.5768	-9.9729
3	**75.818**	-10.879	-7.4299	-9.4775
4	57.6321	-10.6951	-6.1489	-8.8481

The bold font is used to signify the order of the VAR model which is favoured by the respective technique.

Table 4.2.1, above, shows the values of the modified LR test statistic, the AIC, the BIC and the HQIC, corresponding to orders of the VAR model ranging from 0 to 4. Each of the five variants of the VAR model is estimated over the common sample period, 1973q3–2005q1.

The sequential testing procedure uses, at each stage, the five per cent level of significance. The data do not support the inclusion of four quarterly lags on the endogenous variables. However, when concerned with the issue of whether or not a three-period lag on each of the endogenous variables is merited, the computed value of the LR statistic exceeds the associated critical value.

It can be observed from the table that the three information criteria favour a lower-order VAR model. Indeed, on the basis of both the BIC and the HQIC, no lags whatsoever are required on the endogenous variables. In contrast, with respect to the AIC, the minimum value of the statistic accords with a lag length of two quarters

The different methods for deciding upon the optimal length of lag, p, on the endogenous variables consequently do not deliver an identical verdict. Abiding by the choice of the BIC and the HQIC negates the construction of a VAR model altogether. While the application of the AIC results in a preference for two lags on the seven variables, a conservative approach would involve operating in conjunction with a VAR model of order 3, which is the outcome of the sequential testing procedure.[153]

4.3 Granger-Causality Tests

Having estimated the third-order VAR model using OLS, the empirical analysis proceeds with the application of Granger-causality tests. The initial objective is to

[153] In association with a VAR model for which p = 3, that is estimated over the interval, 1973q2-2005q1, a system-wide chi-square test for first-order serial correlation in the error terms yields a probability value of 0.1030. Increasing the order of the VAR model is seen to exacerbate, rather than to reduce, the extent of the problem of autocorrelation.

examine whether or not causality extends from the real price of oil to any of the other six endogenous variables. To be more specific, with respect to the following equation,

$$
\begin{aligned}
x_{jt} = a_{j0} &+ a_{j1,1}x_{1,t-1} + a_{j1,2}x_{1,t-2} + a_{j1,3}x_{1,t-3} \\
&+ a_{j2,1}x_{2,t-1} + a_{j2,2}x_{2,t-2} + a_{j2,3}x_{2,t-3} \\
&+ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\
&+ a_{j7,1}x_{7,t-1} + a_{j7,2}x_{7,t-2} + a_{j7,3}x_{7,t-3} + e_{jt},
\end{aligned} \tag{4.3.1}
$$

$(j = 1, 2, \ldots\ldots, 6)$,

if x_j $(j = 1, 2, \ldots\ldots\ldots, 6)$ signifies an endogenous variable, other than Δlog.(ROILP), and x_7 equates with Δlog.(ROILP) then, for each $j = 1, 2, \ldots\ldots, 6$, an F test is performed of the null hypothesis, Ho: $a_{j7,1} = 0$, $a_{j7,2} = 0$, $a_{j7,3} = 0$, against the alternative Ha: at least one of $a_{j7,i} \neq 0$ $(i = 1, 2, 3)$. The results of the F tests are contained in Table 4.3.1, below.

Table 4.3.1: Results of Granger-Causality Tests Performed in Conjunction with Equation (4.3.1)

	Endogenous Variable		
	Δlog.(GDP)	Δlog.(REER)	Δlog.(RW)
F(3, 106) (probability value)	1.4196 (0.2412)	0.1910 (0.9023)	1.2125 (0.3089)
	Endogenous Variable		
	ΔPINF	ΔTB	ΔLTIR
F(3, 106) (probability value)	1.7513 (0.1610)	0.8073 (0.4926)	2.2076 (0.0915)

Estimation period: 1973q2-2005q1.

The information which is presented in Table 4.3.1 suggests that an earlier change in the value of the oil price variable exerts only a limited influence upon the current values of the remaining six endogenous variables. Indeed, at the ten per cent level, merely one of the computed values of the F statistics is significant. Also, for just two of the six endogenous variables is the associated probability value below 0.2.

In accordance with the methodology which has been proposed, there is, next, undertaken a block exogeneity test. In the context of the VAR model, the purpose of the latter is to assess whether or not past information on the oil price variable is of relevance for determining the current values of any of the other six endogenous variables. With respect to the system of equations for x_{jt} ($j = 1, 2, \ldots\ldots\ldots, 6$), the block exogeneity test takes the form of an LR test of the null hypothesis,

Ho: $a_{j7,i} = 0$ ($j = 1, 2, \ldots\ldots\ldots, 6$; $i = 1, 2, 3$),

against the alternative hypothesis,

Ha: at least one of $a_{j7,i} \neq 0$ (j = 1, 2, ………, 6; i = 1, 2, 3).

The computed value of the LR statistic is 24.785, which is to be contrasted with a critical value that has been extracted from the table of the chi-square distribution, corresponding to 18 degrees of freedom. The five and ten per cent critical values are 28.9 and 26.0, respectively. Hence, at a conventional level of significance, it is not possible to reject Ho in favour of Ha.

Consideration is also given to whether or not the proportional change in the real price of oil is Granger-caused by any of the other six endogenous variables. More specifically, with respect to the equation,

$$\begin{aligned} x_{7t} = a_{70} &+ a_{71,1}x_{1,t-1} + a_{71,2}x_{1,t-2} + a_{71,3}x_{1,t-3} \\ &+ a_{72,1}x_{2,t-1} + a_{72,2}x_{2,t-2} + a_{72,3}x_{2,t-3} \\ &+ \ldots\ldots\ldots\ldots\ldots\ldots \\ &+ a_{77,1}x_{7,t-1} + a_{77,2}x_{7,t-2} + a_{77,3}x_{7,t-3} + e_{7t}, \end{aligned} \tag{4.3.2}$$

for each of j = 1, 2, ..., 6, an F test is performed of the null hypothesis,

Ho: $a_{7j,1} = 0$, $a_{7j,2} = 0$, $a_{7j,3} = 0$,

against the alternative hypothesis,

Ha: at least one of $a_{7j,1} \neq 0$, $a_{7j,2} \neq 0$, $a_{7j,3} \neq 0$.

The results which are obtained from the application of the six F tests are shown in Table 4.3.2, below.

Table 4.3.2: Results of Granger-Causality Tests Performed in Conjunction with Equation (4.3.2)

	Right-Hand-Side Variable		
	Δlog.(GDP)	Δlog.(REER)	Δlog.(RW)
F(3, 106) (probability value)	0.0957 (0.9622)	1.6172 (0.1898)	0.2032 (0.8940)
	Right-Hand-Side Variable		
	ΔPINF	ΔTB	ΔLTIR
F(3, 106) (probability value)	0.2655 (0.8501)	1.4927 (0.2208)	0.0545 (0.9832)

Estimation period: 1973q2-2005q1.

The statistical information which is contained in Table 4.3.2 indicates that the current value of the proportional change in the real price of oil is not significantly affected by past changes in the values of any of the other six endogenous variables. The smallest probability values correspond to the real effective exchange rate and the short-term rate of interest. However, for the remaining four variables, the associated probability value exceeds 0.85.

In conjunction with equation (4.3.2), it is also possible to conduct a more general F test of the null hypothesis that the current value of the oil price variable is unconnected to past values of any of the other six endogenous variables. In terms of mathematics, the validity of

Ho: $a_{7j,1} = 0$, $a_{7j,2} = 0$, $a_{7j,3} = 0$, ($j = 1, 2, ..., 6$),

is considered alongside the alternative hypothesis,

Ha: at least one of $a_{7j,i} \neq 0$, ($i = 1, 2, 3$; $j = 1, 2, ..., 6$).

The computed value of the F(18, 106) statistic is 1.0334, which corresponds to a probability value of 0.4299. Hence, the inference which is drawn is that the value of Δlog.(ROILP)$_t$ is not influenced by any of the past values of any of the six U.K. macroeconomic variables.

4.4 Impulse Response Functions and Forecast Error Variance Decompositions

The estimates of the coefficients within the matrices, A_1, A_2 and A_3, provide an indication of the direct effect of an earlier change in the value of an endogenous variable on the current value of either the same variable or one of the other six variables which enter the system. It must be recognised, though, that the parameter estimates and the results of the associated F and chi-square tests, which have been reported above, do not convey information on the connection between a pair of endogenous variables arising out of the dynamic interactions between all of the variables entering the VAR model. In contrast, for the purpose of evaluating the reaction after a specified number of periods of a given endogenous variable to a shock to either itself or another of the endogenous variables, all of the various interrelationships which comprise the VAR system are combined. Table 4.4.1, below, shows the estimated accumulated responses of each of the six macroeconomic variables after specified numbers of quarters to a one standard deviation innovation in Δlog.(ROILP).

Table 4.4.1: Estimated Accumulated Responses of Endogenous Variables to a One Standard Deviation Innovation in Δlog.(ROILP)

Quarters	Endogenous Variable			
	Δlog.(GDP)	Δlog.(ROILP)	ΔPINF	ΔTB
4	0.0009	0.1625	0.2783	0.4278
8	-0.0012	0.1761	0.2555	0.4701
12	-0.0019	0.1711	0.2600	0.3778
18	-0.0019	0.1709	0.2567	0.3642
24	-0.0019 (0.0022)	0.1710 (0.1162)	0.2564 (0.1522)	0.3652 (0.2500)

Quarters	Endogenous Variable		
	ΔLTIR	Δlog.(RW)	Δlog.(REER)
4	0.3607	-0.0002	0.0076
8	0.3872	0.0005	0.0116
12	0.3789	0.0007	0.0117
18	0.3751	0.0007	0.0116
24	0.3753 (0.2151)	0.0007 (0.0031)	0.0116 (0.0097)

Analytic standard errors are contained in parentheses.
The sequence in which the variables are presented reflects the ordering which was chosen for the Cholesky decomposition.

Upon viewing the contents of Table 4.4.1, it is apparent that, for all of the endogenous variables, the accumulated response to an innovation in the oil price variable has stabilised after twenty-four quarters. Thus, these results would appear to be consistent with the variables entering the VAR model in such a form that the associated time series are stationary. The final row of the table indicates that the ultimate effect of a shock to the oil price variable is negative in terms of the growth of GDP, but positive with respect to the other six variables. When the accumulated responses are studied alongside the respective standard errors, statistically the variables which react most strongly to a disturbance to Δlog.(ROILP) consist of ΔLTIR, ΔPINF and ΔTB.

Table 4.4.2, below, shows the accumulated response of Δlog.(ROILP) after the indicated number of quarters to a one standard deviation innovation in each of the endogenous variables.

Table 4.4.2: Estimated Accumulated Responses of Δlog.(ROILP) to a One Standard Deviation Innovation in Each of the Endogenous Variables

Quarters	Endogenous Variable			
	Δlog.(GDP)	Δlog.(ROILP)	ΔPINF	ΔTB
4	-0.0347	0.1625	0.0009	0.0687
8	-0.0267	0.1761	0.0009	0.0568
12	-0.0245	0.1711	-0.0003	0.0526
18	-0.0251	0.1709	-0.0000	0.0525
24	-0.0252 (22.975)	0.1710 (0.1162)	-0.0000 (0.0219)	0.0527 (0.0315)

(continued)

<u>Quarters</u>	<u>Endogenous Variable</u>		
	ΔLTIR	Δlog.(RW)	Δlog.(REER)
4	0.0122	0.0259	-0.0259
8	0.0114	0.0287	-0.0295
12	0.0122	0.0263	-0.0288
18	0.0117	0.0256	-0.0289
24	0.0117 (0.0264)	0.0256 (0.0371)	-0.0290 (0.0310)

Analytic standard errors are contained in parentheses.
The sequence in which the variables are presented reflects the ordering which was chosen for the Cholesky decomposition.

Again, it is apparent that, after twenty-four quarters, convergence has been achieved with respect to all of the seven estimated accumulated responses. From an observation of the figures in the final row of Table 4.4.2, it can be seen that a positive shock to any of Δlog.(GDP), ΔPINF and Δlog.(REER) provokes a downward movement in Δlog.(ROILP). However, a reference to the associated standard errors reveals that none of these estimated effects are statistically significant. In contrast, the figures indicate a positive relationship between Δlog.(ROILP) and each of ΔTB, ΔLTIR and Δlog.(RW). Also, from examining the estimated responses alongside the respective standard errors, the strongest influence upon the oil price variable is found to be an unexpected movement in ΔTB.

As was mentioned in Chapter Three of this thesis, in combination with an estimated VAR model, there is also the objective of undertaking forecast error variance decompositions. Recall that a forecast error variance decomposition shows the proportion of the unexplained variation in an endogenous variable which is attributable to shocks to itself and the other variables which comprise the VAR system. In order to achieve a situation where, across equations, disturbance terms are orthogonal to one another, reliance is placed upon a Cholesky decomposition. In connection with the latter, the endogenous variables are arranged in the same order as when generating impulse response functions.

Table 4.4.3: Forecast Error Variance Decompositions at the Twenty-Four Quarter Horizon

	Endogenous Variable			
Explained By → Variation In ↓	Δlog.(GDP)	Δlog.(ROILP)	ΔPINF	ΔTB
Δlog.(GDP)	77.854	5.4409	0.8571	4.0523
Δlog.(ROILP)	6.1134	79.262	0.6811	8.0670
ΔPINF	9.5409	3.5430	71.492	5.2111
ΔTB	7.2575	3.5471	1.1587	80.428
ΔLTIR	2.0430	9.8764	2.2208	30.418
Δlog.(RW)	13.789	7.1034	17.851	10.045
Δlog.(REER)	2.4028	1.8016	2.4513	14.491

	Endogenous Variable		
Explained By → Variation In ↓	ΔLTIR	Δlog.(RW)	Δlog.(REER)
Δlog.(GDP)	5.8843	3.1871	2.7242
Δlog.(ROILP)	0.6699	0.9953	4.2109
ΔPINF	2.5232	3.9553	3.7349
ΔTB	2.1921	3.8198	1.5968
ΔLTIR	48.096	5.4326	1.9135
Δlog.(RW)	1.8797	45.511	3.8213
Δlog.(REER)	13.367	2.0265	63.460

Regarding Table 4.4.3, above, the figures which are displayed in the second numerical column indicate that, on the whole, unanticipated movements in the proportional change in the real price of oil make a relatively small contribution towards accounting for the variation in the other endogenous variables. Ignoring the ability of Δlog.(ROILP) to predict future developments in itself, the highest percentage in this column corresponds to ΔLTIR. Δlog.(ROILP) appears to be the third most important variable in terms of forecasting Δlog.(GDP). However, it fulfils the weakest role of all of the endogenous variables with respect to rationalising the behaviour of Δlog.(REER).

The figures which are contained in the second row show the relative contributions which are made by the seven endogenous variables towards explaining the variation in Δlog.(ROILP). Outside of the oil price variable, itself, the highest percentage is associated with ΔTB. The only other variable for which the percentage exceeds 5.0 is Δlog.(GDP).

In order to examine the sensitivity of the estimated impulse responses and variance decompositions to the ordering of the endogenous variables, the sequence is now reversed such that Δlog.(GDP) is regarded as least exogenous and Δlog.(REER) is treated as most exogenous. The results which are obtained following this rearrangement are displayed in Table 4.4.4, Table 4.4.5 and Table 4.4.6.

Table 4.4.4: Estimated Accumulated Responses of Endogenous Variables to a One Standard Deviation Innovation in Δlog.(ROILP) (Reverse Ordering)

Quarters	Endogenous Variable			
	Δlog.(GDP)	Δlog.(ROILP)	ΔPINF	ΔTB
24	-0.0030 (0.0025)	0.1655 (0.0373)	0.2280 (0.0949)	0.2230 (0.2453)

Quarters	Endogenous Variable		
	ΔLTIR	Δlog.(RW)	Δlog.(REER)
24	0.3375 (0.1639)	0.0032 (0.0022)	0.0053 (0.0080)

Analytic standard errors are contained in parentheses.
The sequence in which the variables are presented reflects the reverse of the ordering which was chosen for the Cholesky decomposition.

Table 4.4.5: Estimated Accumulated Responses of Δlog.(ROILP) to a One Standard Deviation Innovation in Each of the Endogenous Variables (Reverse Ordering)

Quarters	Endogenous Variable			
	Δlog.(GDP)	Δlog.(ROILP)	ΔPINF	ΔTB
24	0.0047 (0.0304)	0.1655 (0.0373)	0.0020 (0.0301)	0.0458 (0.0331)

Quarters	Endogenous Variable		
	ΔLTIR	Δlog.(RW)	Δlog.(REER)
24	0.0550 (0.0402)	-0.0249 (340.33)	-0.0331 (114.62)

Analytic standard errors are contained in parentheses.
The sequence in which the variables are presented reflects the reverse of the ordering which was chosen for the Cholesky decomposition.

Table 4.4.6: Forecast Error Variance Decompositions at the Twenty-Four Quarter Horizon (Reverse Ordering)

	Endogenous Variable			
Explained By →	Δlog.(GDP)	Δlog.(ROILP)	ΔPINF	ΔTB
Variation In ↓				
Δlog.(GDP)	62.479	6.0640	1.0842	3.7738
Δlog.(ROILP)	0.7353	71.358	0.8403	4.9968
ΔPINF	7.5849	3.0667	47.709	2.0106
ΔTB	8.8478	2.0759	0.2557	51.591
ΔLTIR	1.3944	8.5438	2.1351	2.0020
Δlog.(RW)	4.5272	3.1771	1.0879	2.2310
Δlog.(REER)	2.6742	0.8283	2.4931	5.8963

	Endogenous Variable		
Explained By →	ΔLTIR	Δlog.(RW)	Δlog.(REER)
Variation In ↓			
Δlog.(GDP)	11.846	12.451	2.3025
Δlog.(ROILP)	5.2328	10.982	5.8552
ΔPINF	3.8680	28.993	6.7681
ΔTB	23.071	5.3808	8.7778
ΔLTIR	62.040	4.5625	19.322
Δlog.(RW)	3.7946	78.500	6.6827
Δlog.(REER)	6.6504	0.8758	80.582

The figures in Table 4.4.4 suggest that, as a consequence of a shock to Δlog.(ROILP), all of the endogenous variables, with the exception of Δlog.(GDP), move in the same direction. It appears, then, that the ordering of the endogenous variables has no effect on the broad reaction of an endogenous variable. In terms of statistical significance, a disturbance to the real price of oil most strongly influences the future behaviour of price inflation and the long-term rate of interest. Again, these results do not seem to be markedly different from the original findings.

The figures which are contained in Table 4.4.5 represent the estimated accumulated changes after six years in Δlog.(ROILP) that are derived from one-standard-deviation innovations in the seven endogenous variables. On the basis of these figures, Δlog.(ROILP) responds negatively to a positive shock to either Δlog.(RW) or Δlog.(REER), yet positively to unexpected developments in the other five variables. Ignoring the estimated accumulated effect after twenty-four quarters on Δlog.(ROILP) of a disturbance to itself, none of the estimates appear to be statistically significant. It seems, then, that, irrespective of the sequence which is chosen for the endogenous variables, the behaviour of Δlog.(ROILP) is largely resistant to unanticipated movements in the six U.K. macroeconomic variables.

The implication of the contents of Table 4.4.6 is that, similar to before, Δlog.(ROILP) has only a limited contribution to make towards explaining the variation in the value of another endogenous variable. A study of the percentages in the second numerical column suggests that Δlog.(ROILP) is most useful in accounting for the behaviour of ΔLTIR. An inspection of the percentages in the second row reveals that, outside of itself, fluctuations in Δlog.(ROILP) are most capably captured by movements in Δlog.(RW). It can be observed that each one of the other five percentages is below 10.0.

4.5 Post-Sample Analysis

In this section, the primary aim is to present statistical information which enables an evaluation of the post-sample performance of the estimated VAR model. The chosen prediction period extends from 2005q2 to 2008q1[154], thereby preceding the banking crisis and the most recent downturn in the U.K. economy. For the purpose of conducting the post-sample analysis, it was necessary to extend all of the original time series. In all cases, reliance was placed on an identical or equivalent data source. However, it must be respected that the operation of splicing was sometimes required for the purpose of achieving consistency.[155]

Prior to presenting statistics relating to the post-sample period, 2005q2–2008q1, it is considered helpful to summarise the within-sample performance of the estimated VAR model. Hence, in Table 4.5.1, there are shown, for each of the seven equations which comprise the VAR system, values of the coefficient of determination (R-squared), the standard error of the regression (S.E.), the AIC and the BIC.

[154] It is considered suitable for the length of the post-sample interval to be approximately ten per cent of that of the estimation period.
[155] All of the data which are employed in this thesis are available on request from the author.

Table 4.5.1: Summary of the Statistical Performance of the Estimated Equations Comprising the VAR Model

Dependent Variable	R-squared	S.E.	AIC	BIC
Δlog.(GDP)$_t$	0.2533	0.0083	-6.6003	-6.1101
Δlog.(ROILP)$_t$	0.1705	0.1660	-0.5987	-0.1085
ΔPINF$_t$	0.4416	0.7358	2.3793	2.8695
ΔTB$_t$	0.2439	1.1706	3.3080	3.7982
ΔLTIR$_t$	0.2195	0.6312	2.0728	2.5629
Δlog.(RW)$_t$	0.3069	0.0108	-6.0604	-5.5702
Δlog.(REER)$_t$	0.2491	0.0336	-3.7963	-3.3062

Estimation period: 1973q2-2005q1.

With reference to the above table, the observation can be made that, by some distance, the sample data on ΔPINF are most effectively accounted for by the past values of the seven endogenous variables. For five of these variables, the value of the R-squared statistic falls within the quite narrow range, 0.22–0.31. The poorest fit is seen to be provided of the data on the proportional change in the real price of oil.

The equations which were obtained from estimation over the interval, 1973q2–2005q1, are subsequently employed in conjunction with the actual values of the right-hand-side variables to produce predictions of the values of the endogenous variables over the following twelve quarters. For each equation, the forecast errors are assembled and combined in order to generate values of the mean square error, the mean error, the mean absolute error, the root mean square error, and the median square error. The values of these summary statistics are shown in Table 4.5.2, below.

Table 4.5.2: Summary of the Post-Sample Performance of the Estimated Equations Comprising the VAR Model

Endogenous Variable	Mean Square Error	Mean Error (s.e)	Mean Absolute Error	Root Mean Square Error	Median Square Error
Δlog.(GDP)	0.11×10^{-4}	0.0009 (0.0009)	0.0027	0.0033	0.41×10^{-5}
Δlog.(ROILP)	0.0114	0.0360 (0.0303)	0.0950	0.1068	0.0083
ΔPINF	0.1670	-0.0250 (0.1230)	0.3303	0.4087	0.0688
ΔTB	0.1608	-0.0482 (0.1200)	0.3195	0.4009	0.0466
ΔLTIR	0.1083	-0.0440 (0.0983)	0.2772	0.3291	0.0815
Δlog.(RW)	0.55×10^{-4}	-0.0014 (0.0022)	0.0060	0.0074	0.18×10^{-4}
Δlog.(REER)	0.48×10^{-3}	-0.0072 (0.0062)	0.0188	0.0219	0.28×10^{-3}

Prediction period: 2005q2-2008q1.
Forecasts are based upon equations which have been estimated over a fixed period, 1973q2-2005q1.
s.e. denotes standard error of the sample mean, which is calculated by applying the square root operator to the ratio of the sample variance of a prediction error to the number of forecasts.

It should be appreciated that the values of the statistics which are presented in Table 4.5.2 will assume greater relevance when a comparison is sought of the empirical performances of different VAR models. However, even when studied in isolation, values of certain statistics permit some comment. For example, the figures which feature in the second numerical column allow the statement that, over the period, 2005q2–2008q1, in five instances, there is a tendency for the value of an endogenous variable to be overpredicted, while, for both Δlog.(GDP) and Δlog.(ROILP), there is a propensity to underpredict. However, it is apparent that there is no situation in which the arithmetic average forecast error (in absolute terms) comes close to equalling two standard errors. Indeed, in five out of seven cases, the value of the standard error exceeds the size of the arithmetic mean. Hence, from the information which is contained in the table, no encouragement is received to declare any of the forecasts as being biased.

A comparison of the values of the root mean square forecast error in Table 4.5.2 with the corresponding values of the standard error of the regression in Table 4.5.1 produces some interesting findings. In the case of each one of the endogenous variables, the value of the root mean square error is observed to be less than that of the standard error of the regression. It can be calculated that, on average, the value of the root mean square error is only fifty-four per cent of that of the standard error of the regression. In moving from the within- to the post-sample period, the greatest improvement in the fit of the data occurs for ΔTB, where the ratio of the root mean square error to the standard error is only 0.34. In contrast, Δlog.(RW) is associated with the most modest advancement, with the value of the ratio being equal to 0.69. Nevertheless, it is possible to pronounce that, in general, the equations which comprise the estimated VAR model provide a superior explanation of the post-sample data on the endogenous variables.[156]

[156] Respect should be paid, though, to the behaviour of the seven endogenous variables exhibiting much greater stability over the interval, 2005q2-2008q1. Indeed, on average, the value of the standard deviation of a variable over the post-sample period is only 42 per cent of its value over the estimation period. In moving from the within- to the post-sample period, the greatest reduction in the standard deviation corresponds to Δlog.(GDP) (= 79 per cent). In contrast, the smallest decline is associated with Δlog.(REER) (= 31 per cent).

4.6 Analysis Performed Over the Shorter Interval, 1982q1-2005q1

Earlier in this chapter, when an examination was undertaken of the stochastic properties of the time series corresponding to the seven endogenous variables, on the occasion of the identification of a diminishing variance, the recommendation was made that the VAR analysis be repeated, adopting the shorter sample period, 1982q1–2005q1. Consequently, in this section, there are reported the results which are founded upon the data over this briefer interval.

Table 4.6.1: Values of the Modified LR Statistic and Information Criteria Corresponding to Different Orders of the Standard VAR Model

Order of VAR Model	LR Statistic	AIC	BIC	HQIC
0	N/A	-15.024	**-14.833**	**-14.947**
1	124.65	**-15.436**	-13.911	-14.820
2	69.762	-15.277	-12.417	-14.122
3	**75.046**	-15.280	-11.086	-13.587
4	65.472	-15.249	-9.7211	-13.017

The bold font is used to signify the order of the VAR model which is favoured by the respective technique.

Table 4.6.1, above, indicates, as before, that the different methods which are available for determining the optimal number of lags on the endogenous variables are not in agreement. A cautious strategy consists of choosing an order of VAR model which corresponds to the highest that is selected through using any individual approach. Consequently, the same as earlier, inferences will be drawn on the basis of the estimated form of a VAR(3) model.[157]

Having applied OLS estimation to each of the equations comprising the VAR(3) model, Granger-causality tests are subsequently performed. Initially, an investigation is undertaken of whether or not the oil price variable Granger-causes any of the six macroeconomic variables. The results of the relevant exclusion tests are shown in Table 4.6.2.

Table 4.6.2: Results of Granger-Causality Tests Performed in Conjunction with Equation (4.3.1) (Reduced Sample Period)

	Endogenous Variable		
	Δlog.(GDP)	Δlog.(REER)	Δlog.(RW)
F(3, 71) (probability value)	0.7583 (0.5212)	0.2544 (0.8580)	0.3619 (0.7807)
	Endogenous Variable		
	ΔPINF	ΔTB	ΔLTIR
F(3, 71) (probability value)	2.1232 (0.1049)	0.0776 (0.9719)	1.3398 (0.2683)

Estimation period: 1982q1-2005q1.

From observing the contents of the Table 4.6.2, it is apparent that none of the values of the F statistics are significant at the ten per cent level. Recall that, when utilising

[157] An encouragement to construct a VAR model of order three, rather than of any higher order, is received from the results of system-wide Lagrange Multiplier tests for (the absence of) first-order serial correlation amongst the disturbance terms. In conjunction with a VAR(3) model, the probability value corresponding to the chi-square test is 0.1571. In contrast, for a VAR(4) model, the probability value is 0.0027.

the full sample period, one of the probability values was below 0.10, while none were less than 0.05. The same as before, the two variables which, in a statistical sense, seem to be the most strongly related to Δlog.(ROILP) are ΔPINF and ΔLTIR, although ΔPINF is now associated with the lower probability value.

In the context of the shortened sample period, it is also possible to perform a block exogeneity test. With respect to the null hypothesis which asserts that past values of Δlog.(ROILP) are of no relevance for determining the current values of any of the six remaining endogenous variables, the computed value of the suitable LR statistic is 16.139. As was reported earlier, the ten per cent critical value corresponding to a chi-square distribution with 18 degrees of freedom is 26.0. Hence, the same as before, at a conventional level of significance, it is not possible to reject the null hypothesis.

Tests can also be conducted in order to assess whether or not the oil price variable is Granger-caused by any of the other variables which enter the VAR system. There are presented in Table 4.6.3 computed values of suitable F statistics, together with the respective probability values.

Table 4.6.3: Results of Granger-Causality Tests Performed in Conjunction with Equation (4.3.2) (Reduced Sample Period)

	Right-Hand-Side Variable		
	Δlog.(GDP)	Δlog.(REER)	Δlog.(RW)
F(3, 71) (probability value)	0.7928 (0.5019)	1.5163 (0.2177)	0.9908 (0.4022)
	Right-Hand-Side Variable		
	ΔPINF	ΔTB	ΔLTIR
F(3, 71) (probability value)	0.2311 (0.8744)	0.8591 (0.4665)	1.5730 (0.2035)

Estimation period: 1982q1-2005q1.

From an examination of the contents of Table 4.6.3, it is apparent that none of the probability values are less than 0.10. Thus, once again, the inference can be drawn that the real price of oil is not Granger-caused by any of the six macroeconomic variables. A contrast from earlier, though, when analysis was undertaken using the full sample period, is that LTIR is associated with the smallest probability value. Previously, having performed the six F tests, LTIR was found to be connected to the highest probability value.

It is also possible to conduct a more general F test of the null hypothesis that, in the context of the equation for $\Delta\text{log.(ROILP)}_t$, every one of the coefficients which is attached to the three lags on the remaining endogenous variables is equal to zero. In relation to this test, the computed value of the F(18, 71) statistic is 1.1603, which yields a probability value of 0.3171. Recall that, when the maximum-length data period was used, the corresponding probability value was 0.4299. Hence, it would seem that, irrespective of whether analysis is undertaken over the full or reduced sample period, on the basis of the results of the F tests, there is little evidence of past macroeconomic developments in the U.K. exerting any influence upon the current behaviour of the real price of oil.

As before, having performed Granger-causality tests, the objective is to estimate impulse responses. More specifically, in Table 4.6.4, there are shown the accumulated responses after twenty-four quarters of the seven endogenous variables to a one standard deviation innovation in Δlog.(ROILP).

Table 4.6.4: Estimated Accumulated Responses of Endogenous Variables to a One Standard Deviation Innovation in Δlog.(ROILP) (Reduced Sample Period)

Quarters	Endogenous Variable			
	Δlog.(GDP)	Δlog.(ROILP)	ΔPINF	ΔTB
24	-0.0007 (0.0024)	0.1599 (0.0415)	0.0622 (0.0474)	0.1475 (0.2881)

Quarters	Endogenous Variable		
	ΔLTIR	Δlog.(RW)	Δlog.(REER)
24	0.1373 (0.1245)	-0.0001 (0.0020)	0.0088 (0.0078)

Analytic standard errors are contained in parentheses.
The sequence in which the variables are presented reflects the ordering which was chosen for the Cholesky decomposition.

An implication of the estimates which are contained in Table 4.6.4 is that, given a shock to the real price of oil, movements occur in ΔPINF, ΔTB, ΔLTIR and

Δlog.(REER) in the same direction and in Δlog.(GDP) and Δlog.(RW) in the reverse direction. With the exception of the reaction of the real wage, these broad responses are in accordance with those which were produced earlier, employing the full sample period. Ignoring the impact on the future behaviour of Δlog.(ROILP), an unanticipated development in the real price of oil does not seem to exert statistically significant effects. The largest value of an estimated response, relative to the associated standard error, is 1.31; additionally, for three of the variables, the estimate is exceeded by the respective standard error. In general, the results corresponding to the period, 1973q2–2005q1, can be considered to be slightly stronger for, in this context, the largest ratio of an estimate to its standard error was equal to 1.74, while, in absolute terms, four of the quotients were in excess of 1.4.

Table 4.6.5 contains estimates of the accumulated responses of Δlog.(ROILP) to shocks to the seven endogenous variables which enter the VAR system. When a comparison is undertaken of the size of the estimated response with the magnitude of the associated standard error, the conclusion can be reached that the real price of oil is largely insensitive to unexpected developments that occur to the macroeconomy of the U.K.. Recall that the same broad verdict emerged from the earlier analysis that was based upon the full sample period.

Table 4.6.5: Estimated Accumulated Responses of Δlog.(ROILP) to a One Standard Deviation Innovation in Each of the Endogenous Variables (Reduced Sample Period)

Quarters	Endogenous Variable			
	Δlog.(GDP)	Δlog.(ROILP)	ΔPINF	ΔTB
24	-0.0330 (0.0497)	0.1599 (0.0415)	-0.0071 (0.0235)	0.0134 (0.0333)

Quarters	Endogenous Variable		
	ΔLTIR	Δlog.(RW)	Δlog.(REER)
24	0.0232 (0.0356)	0.0452 (0.0419)	-0.0408 (0.0349)

Analytic standard errors are contained in parentheses.
The sequence in which the variables are presented reflects the ordering which was chosen for the Cholesky decomposition.

In Table 4.6.6, there can be seen estimated decompositions of forecast error variances corresponding to a twenty-four quarter horizon and the sample period, 1982q1–2005q1. If the figures which are presented in the second column of this table are contrasted with those which are contained in the second column of Table 4.4.3 then it appears that a general consequence of having shortened the sample period is a diminution in the relative contribution which is made by the real price of oil towards explaining the variation in the six macroeconomic indicators. To be more specific, although the oil price variable plays an enhanced role in determining consumer price inflation, its relevance is reduced in terms of accounting for the behaviour of Δlog.(GDP), ΔLTIR and Δlog.(RW).

Table 4.6.6: Forecast Error Variance Decompositions at the Twenty-Four Quarter Horizon (Reduced Sample Period)

	Endogenous Variable			
Explained By → Variation In ↓	Δlog.(GDP)	Δlog.(ROILP)	ΔPINF	ΔTB
Δlog.(GDP)	76.066	2.1228	0.8357	3.7164
Δlog.(ROILP)	11.797	69.017	2.3098	1.7469
ΔPINF	7.5086	6.6836	74.485	1.4968
ΔTB	9.5937	3.3446	9.1107	68.390
ΔLTIR	4.8617	5.1620	3.2793	24.213
Δlog.(RW)	7.4460	2.4233	26.886	4.8409
Δlog.(REER)	11.657	1.7043	5.7343	8.7140

	Endogenous Variable		
Explained By → Variation In ↓	ΔLTIR	Δlog.(RW)	Δlog.(REER)
Δlog.(GDP)	9.4374	2.5495	5.2721
Δlog.(ROILP)	4.3020	4.1838	6.6432
ΔPINF	3.0750	1.6874	5.0634
ΔTB	3.0734	5.0593	1.4285
ΔLTIR	49.719	9.2796	3.4858
Δlog.(RW)	3.8491	51.8627	2.6917
Δlog.(REER)	8.0552	3.5776	60.558

In order to conclude this section, summary statistics are presented in relation to the equations which have been estimated over the abbreviated sample period, 1982q1-2005q1.

Table 4.6.7: Summary of the Statistical Performance of the Estimated Equations Comprising the VAR Model (Reduced Sample Period)

Dependent Variable	R-squared	S.E.	AIC	BIC
Δlog.(GDP)$_t$	0.3672	0.0048	-7.6207	-7.0216
Δlog.(ROILP)$_t$	0.3138	0.1312	-1.0215	-0.4224
ΔPINF$_t$	0.5947	0.4482	1.4362	2.0353
ΔTB$_t$	0.2590	0.8503	2.7166	3.3157
ΔLTIR$_t$	0.3314	0.4485	1.4373	2.0364
Δlog.(RW)$_t$	0.3082	0.0064	-7.0643	-6.4652
Δlog.(REER)$_t$	0.3821	0.0299	-3.9764	-3.3773

Estimation period: 1982q1-2005q1.

If a comparison is performed of the figures which are contained in Table 4.6.7 with those that are presented in Table 4.5.1 then it is apparent that, for every equation, the value of the standard error of the regression has been reduced by virtue of estimating the VAR model over the shorter interval. On average, the size of the standard error in Table 4.6.7 is only seventy per cent of the magnitude of the corresponding standard error in Table 4.5.1. The largest proportional decrease (0.42) relates to the equation for Δlog.(GDP), while the smallest is associated with the equation for Δlog.(REER) (0.11).

In most cases, the fall in the size of the standard error cannot simply be attributed to behaviour of the respective dependent variable being more volatile prior to 1982. A comparison of the values of the R-squared statistic reveals that, on average, as a result of having used a more restricted estimation period, the coefficient of determination increases by ten percentage points. The largest rise is experienced by the equation for ΔPINF (0.15), while, for ΔTB and Δlog.(RW), the improvement is negligible. Substantial differences in the values of the R-squared statistic are suggestive of a misspecification. Within the subsequent empirical analysis, the possibility is explored that the observed instability is the consequence of giving insufficient prominence to the movements in the price of oil which occurred before the U.K. became a significant producer and exporter of crude oil and while this resource was utilised relatively intensively in production.

As a form of caveat, when performing comparisons of different econometric models on the basis of values of measures of goodness of fit, it should be recognised that any of the proposed specifications is likely to incur difficulties in explaining the behaviour of Δlog.(GDP) and ΔPINF during 1979. While the pattern of output growth was distorted by the industrial action which occurred during the so-called Winter of Discontent, movements in the inflation variable were affected by the raising of V.A.T. to a unified level of 15 per cent from 18th June 1979. Previously, rates of 8 and 12.5 per cent had been imposed.

4.7 Empirical Analysis Performed in Conjunction with an Asymmetric VAR Model

4.7.1 Scaled Proportional Increases and Decreases in the Real Price of Oil

The VAR model which has been assembled and estimated in this chapter can be described as linear, on the basis that it incorporates the restriction that the macroeconomic consequences of an increase in the real price of oil are symmetrical to the effects of an identical-size decrease in this variable. However, as has been seen, both theoretical arguments and empirical evidence have been provided in support of the construction of a less constrained system. Indeed, recall that Jimenez-Rodriguez and Sanchez (2005) elected to implement three “leading” approaches in order to characterise the possible non-linear relationship between the real price of oil and the macroeconomy. More specifically, within their study, the modelling strategies of Mork (1989), Lee *et al*. (1995) and Hamilton (1996) were adopted. Empirically, in terms of conventional measures of goodness of fit, the specification which was inspired by the research of Lee *et al*. was regarded as being superior. Hence, as an alternative to the initial VAR model, a system will now be compiled which replaces the endogenous variable, Δlog.(ROILP), by two variables, one of which represents scaled, unanticipated (proportional) increases in the real price of oil (SOPI), while the other indicates scaled, unanticipated (proportional) decreases in the real price of oil (SOPD).

Entering into greater detail, the variables, SOPI and SOPD, are created by firstly modelling $\Delta \log.(ROILP)_t$ (t = 1973q2, 1973q3, ..., 2005q1) using a fourth-order autoregressive process:

$$\Delta \log.(ROILP)_t = \alpha_0 + \alpha_1 \Delta \log.(ROILP)_{t-1} + \alpha_2 \Delta \log.(ROILP)_{t-2} + \alpha_3 \Delta \log.(ROILP)_{t-3} + \alpha_4 \Delta \log.(ROILP)_{t-4} + \varepsilon_t, \quad (4.7.1.1)$$

where ε_t denotes a stochastic error term which possesses a conditional variance, $var.(\varepsilon_t \backslash I_{t-1}) = h_t$. In turn, I_{t-1} signifies all of the information which is available in period t-1.

A GARCH(1, 1) equation is subsequently specified in order to describe the conditional variance of the error term:

$$h_t = \gamma_0 + \gamma_1\varepsilon_{t-1}^2 + \gamma_2 h_{t-1}, \qquad (4.7.1.2)$$

(t = 1973q3, 1973q4, ……, 2005q1).

The residuals which emanate from the estimation of the autoregressive process are denoted by e_t (t= 1973q2, 1973q3, ………, 2005q1), and have the interpretation of unanticipated proportional changes in the real price of oil. Each residual is subsequently scaled through means of division by the estimate of the positive square root of the variance of the corresponding error term ($\sqrt{h^*_t}$), which is founded upon the fitted GARCH(1, 1) model.

A quarterly time series on SOPI is obtained by amending selected values of the time series, $e_t/\sqrt{h^*_t}$. More specifically, negative values are replaced by zero, while all of the other values are retained. Analogously, quarterly data on SOPD are achieved by suitably adjusting the same deflated series of residuals. More precisely, on this occasion, positive values are set to zero, while the remaining values are undisturbed.

The construction of the two separate variables, SOPI and SOPD, to act as substitutes for Δlog.(ROILP), allows for the macroeconomic effects of an increase and a decrease in the real price of oil to be asymmetrical. Additionally, the scaling operation is intended to reflect the feature that a macroeconomic variable will exhibit greater sensitivity to an unexpected movement in the real price of oil, the less volatile has been the behaviour of the latter.

The two newly created time series are displayed diagrammatically below. More specifically, the scaled oil price increases and decreases are shown in Figure 4.7.1.1 and Figure 4.7.1.2, respectively.

Figure 4.7.1.1: Scaled Unanticipated Proportional Increases in the Real Price of Oil

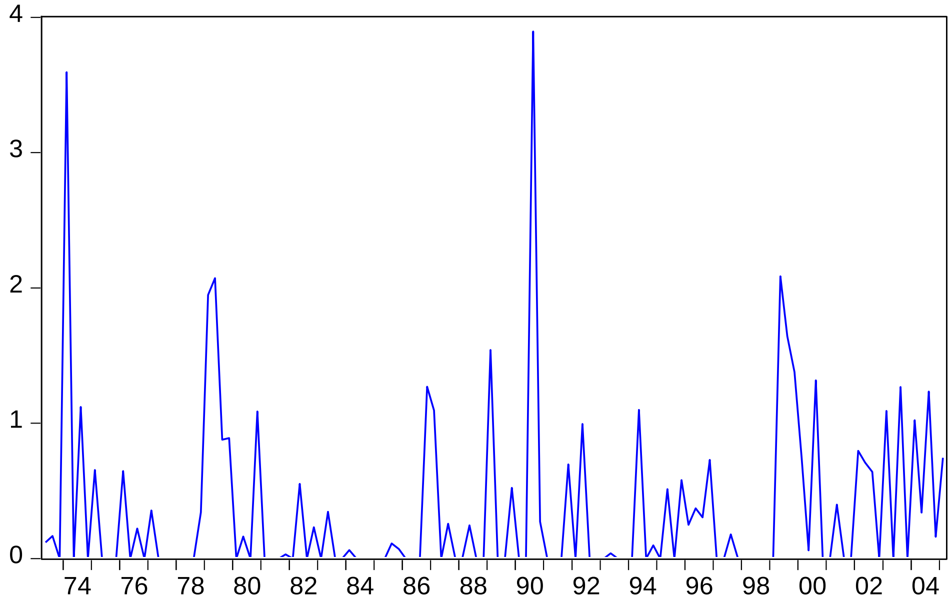
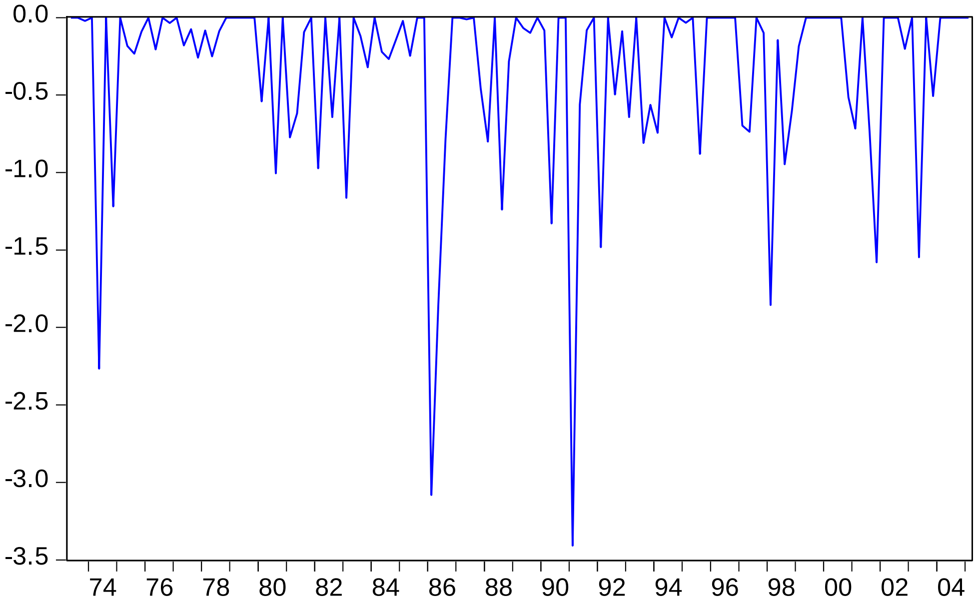


Figure 4.7.1.2: Scaled Unanticipated Proportional Decreases in the Real Price of Oil



In order to assess the stochastic properties of the two time series, both an ADF test and a DF-GLS test are applied to each. On the basis that neither SOPI nor SOPD exhibits a tendency to move upwards or downwards over time, both tests are performed in the context of a model which includes an intercept but not a linear trend term. The results of the unit root tests are contained in Table 4.7.1.1, below.

Table 4.7.1.1: Results of Unit Root Tests Applied to SOPI and SOPD

Unit Root Test		Variable	
		SOPI	SOPD
ADF test			
Computed value of statistic		-6.7082	-5.4496
number of lags		1	3
probability value		0.0000	0.0000
DF-GLS test			
Computed value of statistic		-3.9919	-1.6482
number of lags		5	11
10% critical value		-1.6150	-1.6149

With respect to Table 4.7.1.1, the number of lags on the dependent variable in the test equation has been chosen in accordance with the MAIC. For both variables, irrespective of the type of unit root test which is performed, the inference which is drawn is that the associated time series is stationary.[158] Abiding by these results, it is

[158] A reliance upon a sequential testing procedure for deciding upon the optimal number of lags produces broadly the same conclusions. To be more specific, in only one of the four situations is there agreement on the number of lags, using the two alternative approaches. In spite of these differences,

acceptable to enter SOPI and SOPD into a VAR model without the need for transformation.

4.7.2 Estimation of the Asymmetric VAR System

Equation (3.6.2.3) can be employed to represent the asymmetric VAR model:

$$x_t = A_0 + A_1 x_{t-1} + A_2 x_{t-2} + \cdots + A_p x_{t-p} + e_t. \qquad (3.6.2.3)$$

However, on this occasion, x constitutes an (8 x 1) vector of endogenous variables. The endogenous variables now consist of Δlog.(GDP), Δlog.(REER), SOPI, SOPD, Δlog.(RW), ΔPINF, ΔTB and ΔLTIR. A_0 denotes an (8 x 1) vector which incorporates constant terms, A_i (1, 2, ..., p) indicates an (8 x 8) coefficient matrix, and e_t signifies an (8 x 1) vector of random disturbance terms. The maximum length of lag on the endogenous variables, p, is intended to be sufficient for the error terms to be serially uncorrelated, yet, it is understood that, across the eight equations of the model, the error terms can be contemporaneously correlated. Hence, Σ, the variance-covariance matrix pertaining to the stochastic components, has an order of (8 x 8), and its off-diagonal elements are permitted to be non-zero.

In conjunction with the VAR model, above, a key issue concerns the choice of the number of lags to include on the endogenous variables. As before, allowing for a maximum value of p which is equal to 4, both a sequential testing approach and three

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though, the verdict that is always reached is that the variable under consideration is integrated of order zero.

different information criteria are employed in order to determine whether or not a smaller number of lags is acceptable or preferable.

Table 4.7.2.1: Values of the Modified LR Statistic and Information Criteria Corresponding to Different Orders of the Asymmetric VAR Model

Order of VAR Model	LR Statistic	AIC	BIC	HQIC
0	N/A	-6.6911	**-6.5092**	**-6.6172**
1	146.12	**-6.9294**	-5.2919	-6.2642
2	91.351	-6.7509	-3.6577	-5.4944
3	**83.964**	-6.5668	-2.0180	-4.7190
4	75.425	-6.3634	-0.3589	-3.9242

The bold font is used to signify the order of the VAR model which is favoured by the respective technique.

The values of the modified LR statistic and the three different information criteria are shown in Table 4.7.2.1, above, for different orders of the asymmetric VAR model. Each version of the VAR system has been estimated over the identical period, 1974q2–2005q1.[159]

Upon viewing the contents of the table, it is apparent that there is a lack of unanimity concerning the favoured number of lags on the endogenous variables. On the basis of the values of the BIC and HQIC, there is effectively no justification for assembling a VAR model. In contrast, according to the AIC, one lag is merited on the endogenous variables, while the application of the sequential testing methodology delivers the verdict that as many as three quarterly lags are required. As before, overspecification

[159] The start date is 1974q2 for the reason that the series on SOPI and SOPD only begin in 1973q2.

is regarded as potentially less harmful than underspecification, such that subsequent empirical analysis is performed in conjunction with an estimated form of VAR system which is of order 3.

4.7.3 Granger-Causality Tests

Each of the eight equations comprising the non-linear VAR(3) model is estimated using OLS over an interval that extends from 1974q1 to 2005q1, following which Granger-causality tests are conducted. The initial interest concerns whether or not an oil price variable is responsible for Granger-causing any of the six macroeconomic variables. With respect to the system of equations, below, the endogenous variables, x_7 and x_8, will be regarded as denoting SOPI and SOPD, respectively. By process of elimination, then, x_1, x_2, ..., x_6 will be signifying the six macroeconomic variables.

$$\begin{aligned} x_{jt} = a_{j0} &+ a_{j1,1}x_{1,t-1} + a_{j1,2}x_{1,t-2} + a_{j1,3}x_{1,t-3} \\ &+ a_{j2,1}x_{2,t-1} + a_{j2,2}x_{2,t-2} + a_{j2,3}x_{2,t-3} \\ &+ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ &+ a_{j8,1}x_{8,t-1} + a_{j8,2}x_{8,t-2} + a_{j8,3}x_{8,t-3} + e_{jt}, \end{aligned} \tag{4.7.3.1}$$

$(j = 1, 2, \ldots\ldots, 8)$.

In order to assess whether or not SOPI Granger-causes a macroeconomic variable, for each of j = 1, 2, ..., 6, an F test is performed of the null hypothesis,

Ho: $a_{j7,1} = 0$, $a_{j7,2} = 0$, $a_{j7,3} = 0$,

against the alternative hypothesis,

Ha: at least one of $a_{j7,i} \neq 0$ (i = 1, 2, 3).

Similarly, for the purpose of investigating whether or not Granger-causality extends from SOPD to a macroeconomic variable, for each of j = 1, 2, ..., 6, the null hypothesis,

Ho: $a_{j8,1} = 0$, $a_{j8,2} = 0$, $a_{j8,3} = 0$,

is considered alongside the alternative hypothesis,

Ha: at least one of $a_{j8,i} \neq 0$ (i = 1, 2, 3).

The results of the two sets of exclusion tests are shown in Table 4.7.3.1, below.

Table 4.7.3.1: Results of Granger-Causality Tests Performed in Conjunction with Equation (4.7.3.1)

Oil Price Variable	Endogenous Variable		
	Δlog.(GDP)	Δlog.(REER)	Δlog.(RW)
SOPI	0.9587 (0.4154)	0.9971 (0.3975)	0.7615 (0.5183)
SOPD	0.3857 (0.7635)	1.8517 (0.1427)	0.2452 (0.8646)

(continued)

Oil Price Variable	Endogenous Variable		
	ΔPINF	ΔTB	ΔLTIR
SOPI	3.3259 (0.0227)	0.3015 (0.8243)	1.4193 (0.2416)
SOPD	3.1851 (0.0271)	0.3624 (0.7803)	0.7054 (0.5510)

Estimation period: 1974q1-2005q1.
Computed values of the F(3, 100) statistic are shown in the cells. Associated probability values are contained in parentheses.

The figures which are located in the rows of Table 4.7.3.1 which are associated with SOPI suggest that there is a general lack of a direct influence of past unanticipated increases in the real price of oil on the current values of the six macroeconomic variables. Only in the case of price inflation is the computed value of the F statistic significant at a conventional level. An observation of figures in the rows which are connected to SOPD motivates very much the same type of comment with respect to unexpected decreases in the real price of oil. Only one of the six probability values is less than 0.10. Again, the significant result corresponds to the quarterly percentage rate of consumer price inflation.[160]

In connection with each of the two oil price variables, block exogeneity tests are now performed. To be more specific, first, a modified LR test is undertaken of the null hypothesis that a change in any of $SOPI_{t-1}$, $SOPI_{t-2}$ and $SOPI_{t-3}$ has no effect on the current value of any of the six macroeconomic variables. In terms of mathematics, the null and alternative hypotheses consist of:

Ho: $a_{j7,1} = 0$, $a_{j7,2} = 0$, $a_{j7,3} = 0$ (j = 1, 2, ..., 6); and

[160] In connection with the equation for $\Delta PINF_t$, the sum of the estimated coefficients which are attached to the lags on SOPI is equal to 0.4194. For SOPD, the corresponding figure is -0.2590.

Ha: at least one of $a_{j7,i} \neq 0$ for any j = 1, 2, ..., 6 and i = 1, 2, 3.

The computed value of the LR statistic is 28.539, which is contrasted with a critical value that is extracted from a table of the chi-square distribution corresponding to 18 degrees of freedom. On the basis that the five and ten per cent critical values consist of 28.869 and 25.989, respectively, then it is possible to reject Ho at the ten, but not quite the five, per cent level of significance.

The same form of test is applied in order to investigate whether or not a change in any of $SOPD_{t-1}$, $SOPD_{t-2}$ and $SOPD_{t-3}$ has an effect on the current value of any of the six macroeconomic variables. In this case, the null and alternative hypotheses are:

Ho: $a_{j8,1} = 0$, $a_{j8,2} = 0$, $a_{j8,3} = 0$ (j = 1, 2, ..., 6); and

Ha: at least one of $a_{j8,i} \neq 0$, for any j = 1, 2, ..., 6 and i = 1, 2, 3.

On this occasion, the computed value of the LR statistic is 25.741, which is marginally less than the corresponding ten per cent critical value that was provided above. The inference that can be drawn, having undertaken the two chi-square tests, is that increases in the real price of oil exert a stronger influence than decreases on the U.K. macroeconomy.

Within the framework of the eight-variable, asymmetric VAR model, it is possible to undertake a more general test of whether or not a change in any of $SOPI_{t-1}$, $SOPI_{t-2}$, $SOPI_{t-3}$, $SOPD_{t-1}$, $SOPD_{t-2}$ and $SOPD_{t-3}$ provokes a reaction in the current value of any of the six macroeconomic variables. In this situation, the null and alternative hypotheses take the form of:

Ho: $a_{j7,1} = 0$, $a_{j7,2} = 0$, $a_{j7,3} = 0$, $a_{j8,1} = 0$, $a_{j8,2} = 0$, $a_{j8,3} = 0$ (j = 1, 2, ..., 6); and

Ha: at least one of $a_{jk,i} \neq 0$, for any j = 1, 2, ..., 6, k = 7, 8 and i = 1, 2, 3.

On the basis of the null hypothesis, the LR statistic has a chi-square distribution which is associated with 36 degrees of freedom. The computed value of the statistic is 70.228, which contrasts with a five per cent critical value of 50.964.[161] Having observed the outcomes of the chi-square tests, then, it is possible to conclude that the modification which has been applied to the linear VAR model in order to accommodate asymmetry has succeeded in raising the profile of the real price of oil in relation to the performance of the U.K. macroeconomy.

Attention now turns to whether or not the oil price variables are Granger-caused by any of the six macroeconomic variables entering the VAR system. The relevant equations within the latter are:

[161] The critical value is achieved through linear interpolation, using the five per cent level of significance values corresponding to 30 and 40 degrees of freedom (43.7729 and 55.7585, respectively).

$$x_{jt} = a_{j0} + a_{j1,1}x_{1,t-1} + a_{j1,2}x_{1,t-2} + a_{j1,3}x_{1,t-3} \tag{4.7.3.2}$$

$$+ a_{j2,1}x_{2,t-1} + a_{j2,2}x_{2,t-2} + a_{j2,3}x_{2,t-3}$$

$$+ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots$$

$$+ a_{j8,1}x_{8,t-1} + a_{j8,2}x_{8,t-2} + a_{j8,3}x_{8,t-3} + e_{jt},$$

$(j = 7, 8)$.

In order to assess whether or not past values of an individual macroeconomic variable are influential in determining the current value of SOPI, for each of $j = 1, 2, \ldots\ldots, 6$, an F test is conducted of the null hypothesis,

Ho: $a_{7j,1} = 0$, $a_{7j,2} = 0$, $a_{7j,3} = 0$,

against the alternative hypothesis,

Ha: at least one of $a_{7j,i} \neq 0$ $(i = 1, 2,, 3)$.

Similarly, for SOPD, for each of $j = 1, 2, \ldots\ldots, 6$, the null hypothesis,

Ho: $a_{8j,1} = 0$, $a_{8j,2} = 0$, $a_{8j,3} = 0$,

is considered alongside the alternative hypothesis,

Ha: at least one of $a_{8j,i} \neq 0$ $(i = 1, 2, 3)$.

The results of the twelve F tests are presented in Table 4.7.3.2, below.

Table 4.7.3.2: Results of Granger-Causality Tests Performed in Conjunction with Equation (4.7.3.2)

Oil Price Variable	Right-Hand-Side Variable		
	Δlog.(GDP)	Δlog.(REER)	Δlog.(RW)
SOPI	0.1193 (0.9486)	0.7663 (0.5156)	0.3082 (0.8194)
SOPD	0.7194 (0.5427)	1.6686 (0.1786)	1.3273 (0.2698)
	Right-Hand-Side Variable		
	ΔPINF	ΔTB	ΔLTIR
SOPI	0.4542 (0.7149)	0.3765 (0.7701)	0.3895 (0.7608)
SOPD	0.3124 (0.8163)	0.4392 (0.7255)	0.0680 (0.9768)

Estimation period: 1974q1-2005q1.
Computed values of the F(3, 100) statistic are shown in the cells. Associated probability values are contained in parentheses.

The figures which are incorporated within Table 4.7.3.2 indicate a general lack of significance. The smallest probability value can be found in the second numerical row, and is as high as 0.1786. Regarding the rows of the table which relate to SOPI, it is apparent that every one of the probability values exceeds 0.5. Hence, applying a conventional level of significance, it is not possible to conclude that either SOPI or SOPD is Granger-caused by any one of the six macroeconomic variables.

More wide-ranging F tests are also undertaken. To be more specific, in the context of the equation for $SOPI_t$, an evaluation is performed of the null hypothesis,

Ho: $a_{7j,1} = 0$, $a_{7j,2} = 0$, $a_{7j,3} = 0$ ($j = 1, 2, \ldots\ldots\ldots, 6$),

against the alternative hypothesis,

Ha: at least one of $a_{7j,i} \neq 0$ (i = 1, 2, 3; j = 1, 2, ..., 6).

This amounts to an assessment of whether or not lagged values of any of the macroeconomic variables are of relevance for determining the current value of SOPI.

Similarly, in the context of the equation for $SOPD_t$, the validity of the null hypothesis,

Ho: $a_{8j,1} = 0$, $a_{8j,2} = 0$, $a_{8j,3} = 0$ (j = 1, 2, ………, 6),

is considered in comparison to the alternative hypothesis,

Ha: at least one of $a_{8j,i} \neq 0$ (j = 1, 2, ……, 6; i = 1, 2, 3).

Essentially, then, a judgement is being formed concerning whether or not past values of any of the macroeconomic variables are of any benefit for explaining the variation in the current value of SOPD.

With regard to the first of these joint exclusion tests, the computed value of the F(18, 100) statistic is 0.7504, which is associated with a probability value of 0.7511. For the second of the tests, the computed value of the F(18, 100) statistic is 0.9041, which gives rise to a probability value of 0.5751. Thus, although there is slightly stronger evidence of scaled decreases in the real price of oil being affected by past values of macroeconomic variables, it is not possible to infer that the performance of the U.K. macroeconomy over the previous three quarters has any bearing on the behaviour of either $SOPI_t$ or $SOPD_t$.

4.7.4 Impulse Response Functions and Forecast Error Variance Decompositions

The estimated form of the modified VAR model, accommodating SOPI and SOPD, is now used as a basis for generating impulse response functions and undertaking forecast error variance decompositions. In order to achieve consistency with Jimenez-Rodriguez and Sanchez (2005), the chosen order of the endogenous variables, from most to least exogenous, is Δlog.(GDP), SOPI, SOPD, ΔPINF, ΔTB, ΔLTIR, Δlog.(RW) and Δlog.(REER).

Initially, there are produced the accumulated responses of the endogenous variables to a one standard deviation innovation in SOPI. The results which are obtained are reported in Table 4.7.4.1, below.

Table 4.7.4.1: Estimated Accumulated Responses of Endogenous Variables to a One Standard Deviation Innovation in SOPI

Quarters	Endogenous Variable			
	Δlog.(GDP)	SOPI	SOPD	ΔPINF
4	0.0003	0.7238	0.1634	0.2685
8	-0.0012	0.7994	0.1389	0.2306
12	-0.0022	0.8070	0.1076	0.2347
18	-0.0025	0.8107	0.1002	0.2329
24	-0.0025 (0.0027)	0.8114 (0.1794)	0.0992 (0.1281)	0.2323 (0.1040)

Quarters	Endogenous Variable			
	ΔTB	ΔLTIR	Δlog.(RW)	Δlog.(REER)
4	0.2634	0.2731	0.0006	0.0098
8	0.2735	0.2908	0.0009	0.0113
12	0.1967	0.3088	0.0011	0.0109
18	0.1767	0.3151	0.0011	0.0106
24	0.1740 (0.2597)	0.3155 (0.1802)	0.0011 (0.0023)	0.0106 (0.0080)

Analytic standard errors are contained in parentheses.
The sequence in which the variables are presented reflects the ordering which was chosen for the Cholesky decomposition.

The figures which are listed in the row of Table 4.7.4.1 corresponding to twenty-four quarters ahead indicate that a positive shock to SOPI stimulates a downward movement in Δlog.(GDP) but succeeds in shifting upwards the values of all of the other endogenous variables. However, ignoring the effect of a disturbance to SOPI on its own future development, the only estimated response which is in excess of two standard errors relates to ΔPINF. Also, in the case of ΔLTIR, the calculated response is approximately 1.75 times the size of the associated standard error.

Table 4.7.4.2, below, contains the comparable results for a one standard deviation innovation in SOPD.

Table 4.7.4.2: Estimated Accumulated Responses of Endogenous Variables to a One Standard Deviation Innovation in SOPD

Quarters	Endogenous Variable			
	Δlog.(GDP)	SOPI	SOPD	ΔPINF
4	0.0004	-0.1150	0.6012	-0.0799
8	0.0006	-0.1138	0.5805	-0.0646
12	0.0007	-0.1142	0.5775	-0.0816
18	0.0007	-0.1149	0.5786	-0.0828
24	0.0008 (0.0026)	-0.1149 (0.1614)	0.5787 (0.1149)	-0.0828 (0.0990)

Quarters	Endogenous Variable			
	ΔTB	ΔLTIR	Δlog.(RW)	Δlog.(REER)
4	0.3197	0.0174	-0.0030	0.0072
8	0.3586	-0.0123	-0.0023	0.0097
12	0.3336	-0.0027	-0.0021	0.0090
18	0.3423	-0.0039	-0.0022	0.0091
24	0.3432 (0.2413)	-0.0040 (0.1709)	-0.0022 (0.0022)	0.0091 (0.0075)

Analytic standard errors are contained in parentheses.
The sequence in which the variables are presented reflects the ordering which was chosen for the Cholesky decomposition.

A study of the figures which are incorporated in the row of Table 4.7.4.2 that corresponds to twenty-four quarters ahead suggests that a positive innovation in SOPD inspires a future movement in each of Δlog.(GDP), SOPD, ΔTB and Δlog.(REER) in the same direction. At the same time, though, it appears that decreases are stimulated in the values of SOPI, ΔPINF, ΔLTIR and Δlog.(RW). However, ignoring the consequence for SOPD of an earlier shock to itself, the maximum size of the ratio of the accumulated response to the associated standard error is linked to ΔTB, and is only in the region of 1.42. Interestingly, with respect to ΔPINF, the value which is obtained by dividing the twenty-four quarter accumulated response by the respective standard error is only (minus) 0.84. The greater significance of the estimated effect on ΔPINF of an innovation in SOPI could be construed as support for the policy of allowing for asymmetry when deciding upon the specification of the VAR model.

Consideration is also given to how each of SOPI and SOPD react to unexpected changes in the values of the six macroeconomic variables. The relevant accumulated responses are shown in Table 4.7.4.3 and Table 4.7.4.4, below.

Table 4.7.4.3: Estimated Accumulated Responses of SOPI to a One Standard Deviation Innovation in Each of the Endogenous Variables

Quarters	Endogenous Variable			
	Δlog.(GDP)	SOPI	SOPD	ΔPINF
4	-0.0754	0.7238	-0.1150	0.0800
8	-0.1005	0.7994	-0.1138	0.1147
12	-0.1028	0.8070	-0.1142	0.1229
18	-0.1031	0.8107	-0.1149	0.1245
24	-0.1033 (946.30)	0.8114 (0.1794)	-0.1149 (0.1614)	0.1248 (0.1317)

Quarters	Endogenous Variable			
	ΔTB	ΔLTIR	Δlog.(RW)	Δlog.(REER)
4	0.2759	0.0680	0.1637	0.0302
8	0.3034	0.0935	0.1655	0.0600
12	0.3207	0.0998	0.1748	0.0640
18	0.3258	0.1006	0.1780	0.0640
24	0.3263 (0.1764)	0.1008 (0.1283)	0.1781 (0.1685)	0.0642 (0.1584)

Analytic standard errors are contained in parentheses.
The sequence in which the variables are presented reflects the ordering which was chosen for the Cholesky decomposition.

Table 4.7.4.4: Estimated Accumulated Responses of SOPD to a One Standard Deviation Innovation in Each of the Endogenous Variables

Quarters	Endogenous Variable			
	Δlog.(GDP)	SOPI	SOPD	ΔPINF
4	0.0682	0.1634	0.6012	-0.0389
8	0.0978	0.1389	0.5805	-0.0825
12	0.1050	0.1076	0.5775	-0.0952
18	0.1070	0.1002	0.5786	-0.0986
24	0.1072 (2344.4)	0.0992 (0.1281)	0.5787 (0.1149)	-0.0991 (0.0877)

Quarters	Endogenous Variable			
	ΔTB	ΔLTIR	Δlog.(RW)	Δlog.(REER)
4	0.1085	0.0197	0.0481	-0.0840
8	0.0261	-0.0081	-0.0166	-0.1507
12	-0.0068	-0.0246	-0.0266	-0.1574
18	-0.0152	-0.0274	-0.0308	-0.1589
24	-0.0163 (0.1189)	-0.0279 (0.0873)	-0.0312 (0.1161)	-0.1592 (0.1086)

Analytic standard errors are contained in parentheses.
The sequence in which the variables are presented reflects the ordering which was chosen for the Cholesky decomposition.

An examination of the figures in the rows of Table 4.7.4.3 and Table 4.7.4.4, corresponding to twenty-four quarters ahead, reveals an overall lack of significance. In connection with the U.K. macroeconomic indicators, in only two cases out of twelve is there a clear excess of the size of the estimated accumulated response over the associated standard error. The ratio of the former to the latter is in the vicinity of 1.85 for ΔTB in Table 4.7.4.3 and approximately 1.47 for Δlog.(REER) in Table

4.7.4.4. An interesting aspect of the two tables is that, for the macroeconomic variables, the signs of the final estimates in Table 4.7.4.3 are the complete reverse of those in Table 4.7.4.4.

In conjunction with the estimated form of the asymmetric VAR model, forecast error variance decompositions are now undertaken. Recall that the decomposition of a forecast error variance involves allocating degrees of responsibility for the unexplained variation in an endogenous variable to shocks to itself and the other variables which enter the VAR system. In performing this task, reliance is placed upon a Cholesky decomposition, arranging the variables in the same order as when estimating the accumulated responses.

Table 4.7.4.5: Forecast Error Variance Decompositions at the Twenty-Four Quarter Horizon

	Endogenous Variable			
Explained By → Variation In ↓	Δlog.(GDP)	SOPI	SOPD	ΔPINF
Δlog.(GDP)	75.389	3.7552	1.6731	1.6699
SOPI	2.9653	84.403	2.3241	0.8470
SOPD	4.9351	9.1972	74.558	0.6764
ΔPINF	13.641	5.4603	6.0867	59.282
ΔTB	6.7945	1.7804	2.6361	1.2100
ΔLTIR	0.8738	8.5511	2.6058	5.1263
Δlog.(RW)	11.811	3.8975	3.8319	16.992
Δlog.(REER)	3.4691	3.2600	3.2022	3.4536

(continued)

	Endogenous Variable			
Explained By → Variation In ↓	ΔTB	ΔLTIR	Δlog.(RW)	Δlog.(REER)
Δlog.(GDP)	5.1977	4.6182	3.2527	4.4438
SOPI	5.4482	0.3729	2.1410	1.4982
SOPD	2.4602	1.0503	3.2886	3.8348
ΔPINF	5.4140	1.6797	4.6331	3.8031
ΔTB	78.904	3.3406	3.5213	1.8133
ΔLTIR	30.083	46.294	4.5999	1.8666
Δlog.(RW)	10.952	1.4642	47.921	3.1300
Δlog.(REER)	11.765	10.835	3.7629	60.252

The figures which are reported in Table 4.7.4.5, above, constitute percentages. The key columns are those which show the contributions which are made by SOPI and SOPD towards accounting for the unexplained variation in each of the endogenous variables. In relative terms, the most profound influence of an oil price variable on a macroeconomic variable seems to be the effect which SOPI has on ΔLTIR. Although most of the percentages within the aforementioned columns seem small, it can be noted that, in the row corresponding to ΔPINF, the sum of the percentages which are associated with SOPI and SOPD exceeds 11.5.

Upon viewing the percentages which are presented in the rows of Table 4.7.4.5 which relate to SOPI and SOPD, it can be observed that movements in the macroeconomic variables have relatively little role to play in explaining the behaviour of the two oil price variables. Additionally, while a shock to SOPI is capable of accounting for more than 9 per cent of the variation in SOPD, information on the latter seems to be of comparatively limited worth for the purpose of understanding future developments in the former.

4.7.5 Post-Sample Analysis

In this section, consideration will be given to the empirical performance of the estimated asymmetric VAR model over a post-sample period which extends from 2005q2 to 2008q1. However, it is regarded as convenient to begin by presenting values of statistics which serve to summarise the ability of an estimated equation to fit the within-sample data on the respective endogenous variable.

Table 4.7.5.1: Summary of the Statistical Performance of the Estimated Equations Comprising the Asymmetric VAR Model

Endogenous Variable	R-Squared	S.E.	AIC	BIC
Δlog.(GDP)	0.3207	0.0080	-6.6425	-6.0769
SOPI	0.1587	0.6724	2.2210	2.7867
SOPD	0.1544	0.6129	2.0357	2.6014
ΔPINF	0.5080	0.6914	2.2765	2.8422
ΔTB	0.2023	1.1672	3.3240	3.8897
ΔLTIR	0.2477	0.6251	2.0749	2.6406
Δlog.(RW)	0.3070	0.0109	-6.0324	-5.4668
Δlog.(REER)	0.2867	0.0330	-3.8095	-3.2438

Estimation Period: 1974q1-2005q1

In spite of estimation periods not being identical, where possible, a comparison will be undertaken of the figures which are included in Table 4.7.5.1, above, with those which are contained in Table 4.5.1 in an earlier section of this chapter. In general, the replacement in the VAR model of Δlog.(ROILP) by SOPI and SOPD does not seem to have produced a distinct improvement in the fit of the within-sample data on the macroeconomic variables. In absolute terms, the largest increases in the value of the coefficient of determination are associated with the equations for Δlog.(GDP) and ΔPINF.[162] In the case of Δlog.(REER), the value of the R-squared statistic rises by 0.0376. However, for the remaining three macroeconomic variables, either a more modest advancement or deterioration is apparent.

With reference to the value of the standard error of the regression, there can be observed only one instance of a reduction which is in excess of 0.01. More specifically, in the case of the equation for ΔPINF, the value of the standard error falls by 0.0444, from 0.7358 to 0.6914. Also, consumer price inflation can be identified as the only one of the six macroeconomic variables for which the values of both information criteria decrease in moving from the linear to the asymmetric specification. For both GDP and the real effective exchange rate, a fall in the value of the AIC is coupled with a rise in the value of the BIC. Moreover, for each of the real wage and the short- and long-term rates of interest, the asymmetric equation is connected to higher values of both the AIC and BIC.

The eight equations which comprise the estimated version of the asymmetric VAR model are employed to generate forecasts of the values of the dependent variables over the interval, 2005q2–2008q1. The predictions are then suitably combined with the respective actual values of the variables in order to produce eight series of forecast errors. Each series of forecast errors is summarised by calculating values of

[162] Increases of 0.0674 and 0.0664, respectively.

the mean square error, the mean error, the mean absolute error, the root mean square error, and the median square forecast error. For each of the endogenous variables, the values of the five summary statistics are displayed in Table 4.7.5.2.

Table 4.7.5.2: Summary of the Post-Sample Performance of the Estimated Equations Comprising the Asymmetric VAR Model

Endogenous Variable	Mean Square Error	Mean Error (s.e)	Mean Absolute Error	Root Mean Square Error	Median Square Error
Δlog.(GDP)	0.10×10^{-4}	0.0002 (0.0010)	0.0025	0.0032	0.60×10^{-5}
SOPI	0.2587	0.1597 (0.1456)	0.4124	0.5086	0.1163
SOPD	0.1733	0.1518 (0.1169)	0.3728	0.4163	0.1536
ΔPINF	0.2370	0.0019 (0.1468)	0.3818	0.4868	0.0592
ΔTB	0.1377	-0.0134 (0.1118)	0.3042	0.3711	0.0624
ΔLTIR	0.0887	-0.0010 (0.0898)	0.2460	0.2979	0.0332
Δlog.(RW)	0.0001	-0.0011 (0.0022)	0.0058	0.0073	0.15×10^{-4}
Δlog.(REER)	0.0006	-0.0100 (0.0069)	0.0204	0.0251	0.0004

Prediction period: 2005q2-2008q1.
Forecasts are based upon equations which have been estimated over a fixed period, 1974q1-2005q1.
s.e. denotes standard error of the sample mean, which is calculated by applying the square root operator to the ratio of the sample variance of a prediction error to the number of forecasts.

A study of the figures in the second numerical column of Table 4.7.5.2 reveals that, with respect to the first four endogenous variables, there is a tendency to underpredict, while, for the second four variables, there is a propensity for the forecast to exceed the corresponding actual value. However, in absolute terms, all eight of the values of the ratio of the arithmetic mean of the forecast errors to its standard error are less than 1.45. Furthermore, for five of the variables, the size of the standard error is greater than that of the arithmetic average. Consequently, on the basis of the information which is contained in the above table, it is not possible to pronounce any of the forecasts as being biased.

In terms of the ability to explain the within-sample data, there was observed to be, at best, only a small gain to be made from modifying the original VAR model to allow for asymmetry. By comparing corresponding values of root mean square errors, an assessment will now be formed of whether or not the amendment which was applied to the linear model succeeds in enhancing the accuracy of the post-sample predictions. Specifically, on the basis of a consideration of the figures which are located in the fourth column of Table 4.7.5.2, above, alongside those which are contained in the same column of Table 4.5.2, in the preceding section, it is not possible to pronounce that the adaptation of the initial VAR model has the effect of producing a general improvement in the quality of the forecasts of the values of the macroeconomic variables. Although, for both ΔTB and ΔLTIR, there can be observed a marked decrease in the value of the root mean square forecast error, for both ΔPINF and Δlog.(REER), there transpires an apparent decline in the standard of the predictions, while, for both Δlog.(GDP) and Δlog.(RW), there is virtually no change.

Whether or not there is a significant difference between corresponding values of the mean square error can be formally investigated by performing the test which was advocated by Harvey *et al*. (1997). More specifically, for each of the six macroeconomic variables, a two-tailed test will be conducted of the null hypothesis, Ho: $E[d_t] = 0$, where $d_t = e_{it}^2 - e_{jt}^2$, and e_{it} and e_{jt} signify the prediction errors corresponding to the linear and asymmetric specifications, respectively.

In the context of one-step-ahead forecasts being generated, the test statistic,

$$S_1^* = \sqrt{\frac{(n-1)}{n}}\, S_1, \tag{4.7.5.1}$$

where

$$S_1 = \sqrt{\frac{d^*}{s.e.(d^*)}}. \tag{4.7.5.2}$$

With reference to the above two definitions, d* denotes the arithmetic average value of d_t over the forecast interval, t = T+1, T+2, ……, T+n, while s.e.(d*) signifies its standard error. Recall that Harvey *et al.* (1997) proposed contrasting the computed value of the test statistic with a critical value, which is extracted from the table of the t distribution, which is associated with n–1 degrees of freedom.

Table 4.7.5.3 shows, for each of the six macroeconomic variables, the computed value of S_1^*. For a two-tailed test, the corresponding five and ten per cent critical values with which this should be contrasted are 2.201 and 1.796, respectively.

Table 4.7.5.3: Computed Values of the S_1^* Statistic for the purpose of Testing for the Equality of the Forecast Accuracy of the Linear and Asymmetric VAR Models

	Endogenous Variable					
	Δlog.(GDP)	ΔPINF	ΔTB	ΔLTIR	Δlog.(RW)	Δlog.(REER)
Value of S_1^*	0.3927	-1.5937	0.7588	1.5445	0.5583	-1.9093

With reference to the figures which are displayed in Table 4.7.5.3, a positive (negative) value is indicative of the asymmetric model being associated with a superior (an inferior) forecasting performance. Thus, confirmation is received that there are four circumstances in which the asymmetric specification yields the smaller mean square forecast error. However, following application of the test which was favoured by Harvey *et al*. (1997), in none of these situations can the difference between the respective values be classed as significant at a conventional level. In contrast, there are seen to be only two situations in which the non-linear equation generates the greater mean square forecast error, However, these two cases correspond to, in absolute terms, the largest values of the test statistic. Moreover, with respect to the endogenous variable, Δlog.(REER), the computed value of S_1^* is significant at the ten per cent level.

It may be recalled from Chapter Three that, in the presence of at least two rival models, it is possible to perform a test of forecast encompassing. Indeed, more specifically, for the purpose of testing the null hypothesis that the forecasts of model i encompass those of model j, Harvey *et al*. (1998) proposed conducting a test which again involved computing the value of the statistic, S_1^*. However, in this context, d_t ($t = T+1, T+2, \ldots\ldots, T+n$) is defined as $e_{it}(e_{it} - e_{jt})$. Additionally, it is appropriate to perform a one-tailed t test, such that the specification of the alternative hypothesis is Ha: $E[d_t] > 0$.[163]

In relation to tests of the null hypothesis that the forecasts emanating from the linear equation encompass those which are founded upon the corresponding asymmetric equation, the computed values of the S_1^* statistic are shown in Table 4.7.5.4. Relevant five and ten per cent critical values consist of 1.796 and 1.363, respectively, appreciating that there are eleven degrees of freedom.

Table 4.7.5.4: Computed Values of the S_1^* Statistic for the purpose of Testing for Forecast Encompassing in relation to Linear and Asymmetric VAR Models

	Endogenous Variable					
	Δlog.(GDP)	ΔPINF	ΔTB	ΔLTIR	Δlog.(RW)	Δlog.(REER)
Value of S_1^*	0.8409	-1.0386	1.1907	2.3489	0.7996	-1.3896

From a study of the figures which are presented in Table 4.7.5.4, it appears that, when conducting the encompassing test at either the five or ten per cent level of significance, there is only one instance of a rejection of the null hypothesis. Solely for the endogenous variable, ΔLTIR, is the computed value of S_1^* greater than the five or ten per cent critical value. For each of the other five macroeconomic variables, it is possible to draw the inference that the forecasts which evolve from the linear equation encompass those which are generated by the respective asymmetric equation. Thus, for a clear majority of the macroeconomic variables, the information

[163] It may be recollected that the form of test that is being described is suitable for when forecasts are unbiased. However, to this point in the empirical analysis, there has been a general lack of statistical evidence to contradict this property.

content of the forecasts which are produced by the asymmetric model has been found to be no greater than that of the predictions which stem from the linear model.

4.7.6 Results Relating to a Reduced Sample Period

Both within- and post-sample analyses have now been conducted in conjunction with the asymmetric VAR model. From the results which have been obtained, there would seem to be only patchy evidence in support of the asymmetric specification being superior to the linear system.

It may be recalled that, when OLS estimation was applied to the linear VAR model, there was found to be a general improvement in goodness of fit which was achieved by virtue of issuing the sample period with a later start date.[164] On the basis that the value of the coefficient of determination increased in every case, it was not possible to attribute such a development simply to the behaviour of the endogenous variables having been more volatile before 1982. In connection with the two variables, Δlog.(GDP) and ΔPINF, it was recognised that events which occurred in 1979 contributed towards it being more difficult to explain their variation over the full data period. Consequently, for these two endogenous variables, at least, it would seem to be appropriate to contrast the within-sample performances of the respective linear and asymmetric regression functions over the interval, 1982q1-2005q1. For all of the endogenous variables which enter the asymmetric VAR model, summary statistics corresponding to this shorter interval are presented in Table 4.7.6.1.

[164] As indicated by a fall in the value of the standard error of the regression.

Table 4.7.6.1: Summary of the Statistical Performance of the Estimated Equations Comprising the Asymmetric VAR Model (Reduced Sample Period)

Endogenous Variable	R-Squared	S.E.	AIC	BIC
Δlog.(GDP)	0.3690	0.0049	-7.5590	-6.8782
SOPI	0.1988	0.6282	2.1327	2.8135
SOPD	0.3664	0.5867	1.9959	2.6767
ΔPINF	0.6389	0.4323	1.3853	2.0661
ΔTB	0.2797	0.8566	2.7528	3.4336
ΔLTIR	0.3612	0.4479	1.4562	2.1370
Δlog.(RW)	0.3559	0.0063	-7.0713	-6.3905
Δlog.(REER)	0.4067	0.0300	-3.9525	-3.2717

Estimation Period: 1982q1-2005q1

With reference to the full sample period, it may be recollected that, for Δlog.(GDP), the movement from the linear to the asymmetric specification delivered an increase in the value of the R-squared statistic of almost seven percentage points. Additionally, the values of the standard error of the regression and the AIC both fell. In contrast, when the period of analysis is restricted, there is witnessed (to two decimal places) no improvement at all in the value of the coefficient of determination and a deterioration in the values of the standard error, the AIC and the BIC. Consequently, any benefit that was previously understood to be gained by allowing for asymmetry in relating output growth to changes in the real price of oil would seem to have been extinguished.

In the case of ΔPINF, it is apparent that the superiority of the asymmetric equation is maintained, to a certain extent, when the length of the estimation period is reduced.[165] With respect to the full sample period, progression from the linear to the asymmetric model produced an increase in the value of the coefficient of determination which was equal to almost seven percentage points. Additionally, the values of the standard error of the regression and the two information criteria fell. Concerning the shortened data period, the introduction of asymmetry yields an improvement in the value of the R-squared statistic (by more than four percentage points), a decrease in the values of the standard error and the AIC, although a rise in the value of the BIC. However, in the previous sub-section, the predictive ability of the asymmetric equation was observed to be inferior to that of its linear counterpart, which still offers encouragement to consider other modifications.

4.8 Empirical Analysis Performed in Conjunction with an Extended Version of the Linear VAR Model

4.8.1 Historical Behaviour of the U.K.'s Consumption and Exports of Crude Oil

In earlier sections of this chapter, analysis has been undertaken in conjunction with the linear VAR model which featured in the article by Jimenez-Rodriguez and Sanchez (2005). In general, the evidence which was obtained showed, at best, only a weak relationship between the price of oil and U.K. macroeconomic performance. However, the instability which was detected gave rise to a concern over whether or not the linear VAR model constituted a suitable framework for the econometric investigation.

[165] Table 4.7.6.1 should be contrasted with Table 4.6.7.

Consequently, in section 4.7, there was constructed and estimated an alternative (non-linear) VAR model, which also entered the study by Jimenez-Rodriguez and Sanchez. The sample data appeared to provide support for the policy of allowing for the effects of an increase and a decrease in the real price of oil to be asymmetrical (especially in respect of consumer price inflation).[166] However, the quality of the predictions which were generated by the non-linear VAR system was found to be no different from that of the forecasts which were produced by the linear model. Moreover, the asymmetric model was seen to suffer from the same deficiency as its rival, given that a marked contrast could be observed in its ability to explain the behaviour of the endogenous variables over different time periods.

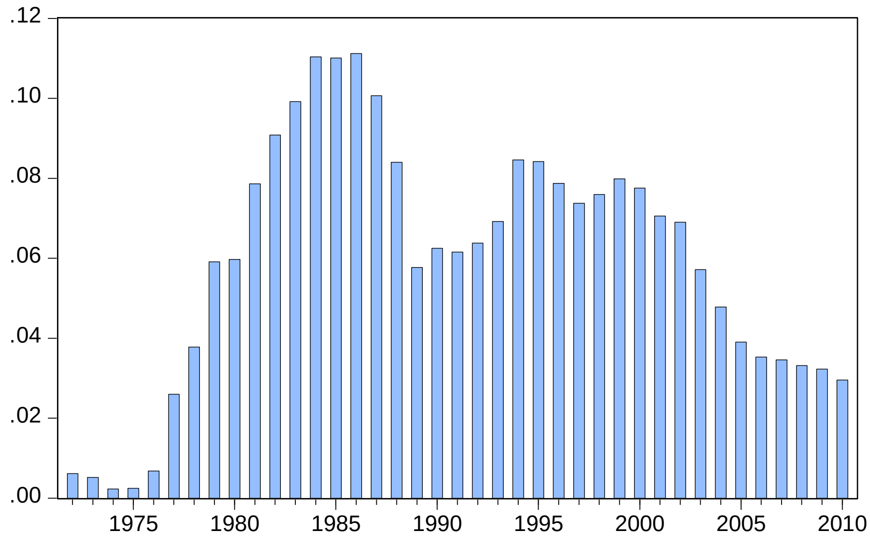
A characteristic of both the linear and the asymmetric VAR models, which may be regarded as being unduly restrictive when analysing data on the U.K., is the implicit assumption that the effect of a change in the price of oil on a macroeconomic indicator is unchanged over time.[167] However, there is reason to believe that, since the beginning of the sample period, 1972q1, the U.K. economy has become more robust to a given-size shock to the real price of oil. As the graphs in Chapter One revealed,[168] over the course of the past approximately forty years, the U.K. has become more efficient in terms of its use of crude oil, as well as a significant exporter of this commodity.

As was indicated in the introduction to this thesis, the U.K.'s consumption of crude oil (million tonnes), relative to the value of its G.D.P. (£billion, 2009 prices),

[166] For example, see the figures in Table 4.7.4.1 and Table 4.7.4.2.
[167] It should be accepted that, in the case of the non-linear model, the veracity of this statement depends upon there being no alteration in the volatility of the real price of oil.
[168] Specifically, Figure 1.2 and Figure 1.3.

decreased (albeit not quite continuously) from 0.19, in 1972, to 0.05, in 2010. Additionally, as shown in Figure 4.8.1.1, over the same period, the ratio of the U.K.'s exports of crude oil (million tonnes) to its G.D.P. increased from 0.006 to 0.030. More specifically, the U.K. first became a significant exporter of crude oil in 1977.[169] The value of the ratio subsequently peaked in 1986 (= 0.111). However, between 1986 and 1989, there occurred a 48 per cent reduction, which was followed by a 46 per cent rise to 1995. Thereafter, the trajectory was predominantly downwards, with a decline being witnessed in each of the final eleven years.

Figure 4.8.1.1: Ratio of the U.K.'s Exports of Crude Oil (million tonnes) to G.D.P. (£billion, 2009 prices)



It is possible to take advantage of the data which are available on the consumption and exports of crude oil by the U.K. to augment the earlier two VAR models in such a way that they incorporate the following characteristics:

[169] From 1976 to 1977, the ratio of oil exports to G.D.P. rose from 0.007 to 0.026.

- the lower (higher) is the degree of intensity with which the U.K. uses crude oil in production, the smaller (greater) will be the impact of any change in the real price of oil on macroeconomic performance;
- the larger (smaller) is the ratio of the U.K.'s exports of crude oil to its G.D.P., the less (more) responsive will be the macroeconomy of the U.K. to a disturbance to the real price of oil.

With regard to, in particular, the linear VAR model that was constructed, it would seem that an efficient approach towards accommodating both of these features is by attaching as a weight to Δlog.(ROILP) the ratio of the U.K.'s exports to its consumption of crude oil. The resultant variable will be denoted by W*Δlog.(ROILP) and is allowed to reside alongside Δlog.(ROILP) within the VAR system. The presence of this additional variable is essentially allowing the parameter which is attached to Δlog.(ROILP) to vary in accordance with changes that occur in the U.K.'s consumption and exports of crude oil.[170]

Figure 4.8.1.2, below, shows the annual time-series data on the ratio of the U.K.'s exports to its consumption of crude oil. A quarterly time series was acquired through implementing the technique of interpolation, which was subsequently employed to produce the data on W*Δlog.(ROILP), which are displayed in Figure 4.8.1.3.

[170] A preference is exhibited for combining the consumption and exports of crude oil to form a single measure, rather than representing the two variables separately, in order to preserve degrees of freedom.

Figure 4.8.1.2: Ratio of the U.K.'s Exports to its Consumption of Crude Oil (both expressed in tonnes)

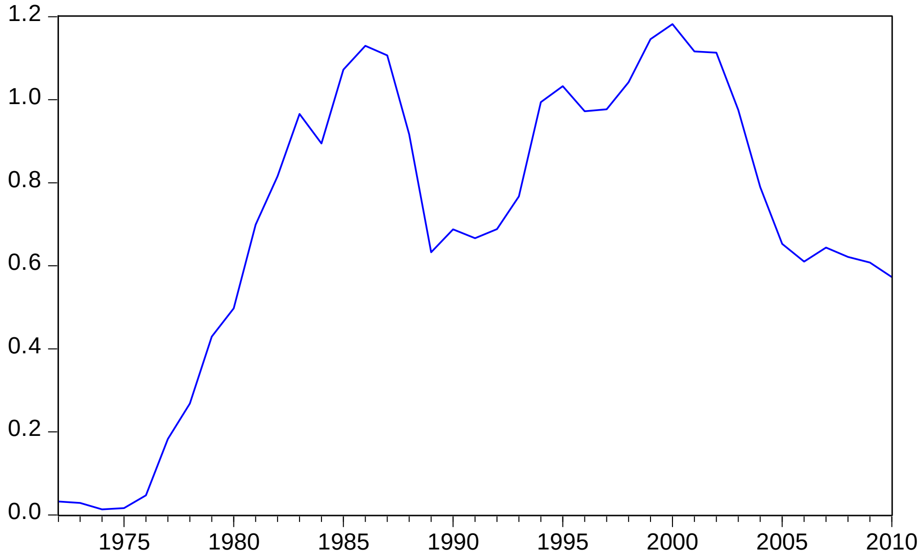
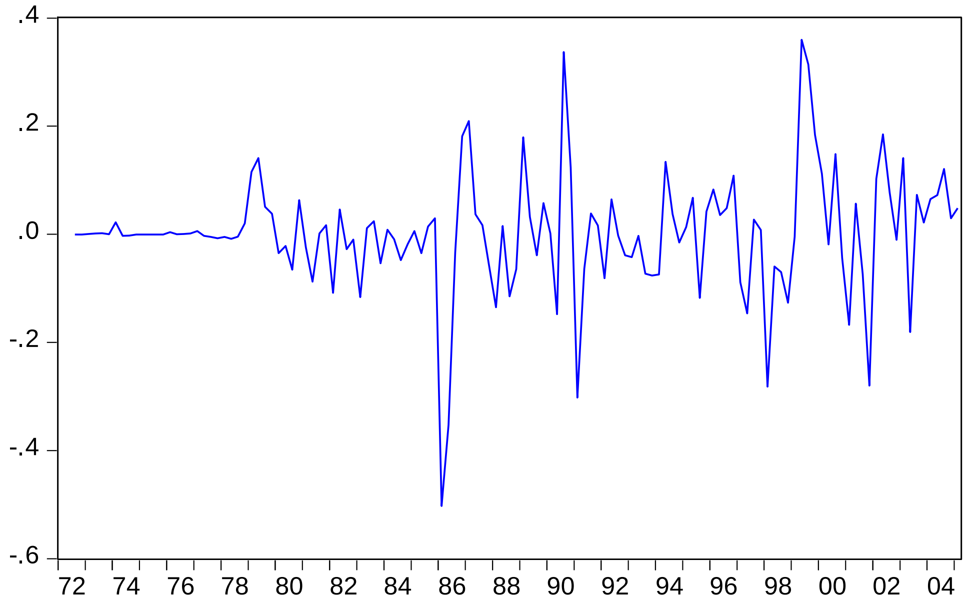


Figure 4.8.1.3: Quarterly Data on the Weighted Oil Price Measure



The line graph in Figure 4.8.1.2 indicates that the peak impact of a change in the price of oil on the U.K. macroeconomy is imposed as occurring in 1974. In contrast, the weakest effect is associated with the year 2000. Since the turn of the century, the value of the ratio has been predominantly falling, such that, in 2010, it represented only forty-eight per cent of its maximum.

The quarterly data on W*Δlog.(ROILP) are displayed in Figure 4.8.1.3 over the period, 1972q3-2005q1. The stochastic properties of the series are examined through performing the familiar unit root tests, the results of which are presented in Table 4.8.1.1, below. On account of the apparent constancy of the mean, the ADF and DF-GLS tests are conducted with allowance for an intercept but not a linear trend term.

Table 4.8.1.1: Results of Unit Root Tests Applied to W*Δlog.(ROILP)

Unit Root Test		Deterministic Terms Allowed For In The Procedure
		Intercept/No Trend
ADF test		
Computed value of statistic		-8.7618
number of lags		0
probability value		0.0000
DF-GLS test		
Computed value of statistic		-8.7955
number of lags		0
10% critical value		-1.6151

With respect to the contents of Table 4.8.1.1, for both of the tests, the number of lags on the dependent variable has been selected to be in accordance with the MAIC. Note that, when reliance is alternatively placed upon a sequential testing procedure, in both situations, four quarterly lags are considered to be optimal. Although, in both cases, there occurs a reduction in the absolute value of the test statistic, it is still possible to reject the null hypothesis at a very low level of significance. Hence, there is a statistical justification for adding W*Δlog.(ROILP) to the linear VAR model, without having undertaken any transformation.

4.8.2 Specification and Estimation of the Augmented Linear VAR Model

Equation (3.6.2.3) can be employed to represent the augmented version of the linear VAR model:

$$x_t = A_0 + A_1 x_{t-1} + A_2 x_{t-2} + \cdots + A_p x_{t-p} + e_t. \qquad (3.6.2.3)$$

However, on this occasion, x denotes a vector of endogenous variables which is of order (8 x 1). The endogenous variables consist of Δlog.(GDP), Δlog.(REER), Δlog.(ROILP), W*Δlog.(ROILP), Δlog.(RW), ΔPINF, ΔTB and ΔLTIR. A_0 constitutes an (8 x 1) vector of constant terms. A_i (i = 1, 2, ………, p) signifies a coefficient matrix of order (8 x 8). Finally, e_t is an (8 x 1) vector of random serially uncorrelated disturbance terms, for which the variance-covariance matrix, Σ, is of order (8 x 8). With respect to the latter, it is appreciated that the off-diagonal elements are not constrained to being equal to zero.

As before, for the purpose of deciding upon the order of the VAR model, having imposed a maximum lag length of 4 quarters, reference is made to the values of three different information criteria, as well as the outcome of a sequential testing procedure. The relevant values of the modified LR statistic, as well as the AIC, BIC and HQIC are shown in Table 4.8.2.1, below.

Table 4.8.2.1: Values of the Modified LR Statistic and Information Criteria Corresponding to Different Orders of the Augmented Linear VAR Model

Order of VAR Model	LR Statistic	AIC	BIC	HQIC
0	N/A	-13.022	**-12.843**	**-12.950**
1	175.92	-13.505	-11.893	-12.850
2	125.78	**-13.641**	-10.595	-12.403
3	93.594	-13.551	-9.0716	-11.731
4	**88.218**	-13.481	-7.5689	-11.079

The bold font is used to signify the order of the VAR model which is favoured by the respective technique.

With regard to the information which is contained in Table 4.8.2.1, it should be recognised that each of the five variants of VAR model has been estimated over a common sample period, 1973q3–2005q1. From a study of the table, it is apparent that neither the BIC nor the HQIC support the construction of a VAR system. In contrast, the AIC exhibits a preference for admitting to the system two lags on the endogenous variables. However, upon implementing a sequential testing procedure, involving computation of the values of a modified LR statistic, the verdict which is reached is that a VAR model of order four most adequately characterises the data. As before, the policy is adopted of proceeding to perform analysis in conjunction with the highest order of VAR model that arises from the application of the four different methods of selection.

4.8.3 Granger-Causality Tests

Consequently, the extended linear VAR model is estimated, using OLS, having included four lags on the endogenous variables. Subsequently, Granger-causality tests are undertaken in order to assess whether or not past information on the real price of oil is beneficial for the purpose of explaining the variation over the sample period in the current values of the macroeconomic variables.

In order to be more precise, the VAR(4) model is presented as:

$$\begin{aligned} x_{jt} = a_{j0} &+ a_{j1,1}x_{1,t-1} + a_{j1,2}x_{1,t-2} + a_{j1,3}x_{1,t-3} + a_{j1,4}x_{1,t-4} \\ &+ a_{j2,1}x_{2,t-1} + a_{j2,2}x_{2,t-2} + a_{j2,3}x_{2,t-3} + a_{j2,4}x_{2,t-4} \\ &+ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ &+ a_{j8,1}x_{8,t-1} + a_{j8,2}x_{8,t-2} + a_{j8,3}x_{8,t-3} + a_{j8,4}x_{8,t-4} + e_{jt}, \end{aligned} \tag{4.8.3.1}$$

$(j = 1, 2, \ldots\ldots, 8)$.

For convenience, x_1, x_2, ………, x_6 will be regarded as denoting the six macroeconomic variables, while x_7 and x_8 refer to Δlog.(ROILP) and W*Δlog.(ROILP), respectively.

The initial concern is with whether or not Δlog.(ROILP) Granger-causes any of the six macroeconomic variables. For this purpose, for each of $j = 1, 2, \ldots\ldots, 6$, an F test is performed of the null hypothesis,

Ho: $a_{j7,1} = 0$, $a_{j7,2} = 0$, $a_{j7,3} = 0$, $a_{j7,4} = 0$, against the general alternative hypothesis,

Ha: at least one of $a_{j7,i} \neq 0$, (i = 1, 2, 3, 4).

The results of the Granger-causality tests are shown in Table 4.8.3.1, below.

Table 4.8.3.1: Results of Granger-Causality Tests Performed in Conjunction with Equation (4.8.3.1)

	Endogenous Variable		
	Δlog.(GDP)	Δlog.(REER)	Δlog.(RW)
F(4, 94) (probability value)	1.5256 (0.2010)	1.8413 (0.1274)	2.5653 (0.0432)
	Endogenous Variable		
	ΔPINF	ΔTB	ΔLTIR
F(4, 94) (probability value)	7.4240 (0.0000)	3.1772 (0.0170)	7.8129 (0.0000)

Estimation period: 1973q3-2005q1.

A more general system test is also undertaken of the null hypothesis that none of the lagged values of Δlog.(ROILP) are of any merit in determining the current values of any of the six macroeconomic variables. In terms of mathematics, a modified LR test is applied to

Ho: $a_{j7,1} = 0$, $a_{j7,2} = 0$, $a_{j7,3} = 0$, $a_{j7,4} = 0$, (j = 1, 2, ………, 6),

in comparison to the alternative hypothesis, Ha: at least one of $a_{j7,i} \neq 0$, (j = 1, 2, ………, 6; i = 1, 2, 3, 4).

The computed value of the LR statistic is 104.65, which should be contrasted with a critical value that is extracted from the table of the chi-square distribution, corresponding to 24 degrees of freedom. Given that the 0.5 per cent critical value is equal to 45.56 then it is apparent that the null hypothesis can be rejected at a very low level of significance.

On the basis of the results which have been reported, above, it seems that the augmentation which has been applied to the linear VAR model has succeeded in raising the prominence of the price of oil in terms of its contribution towards the performance of the U.K. macroeconomy. From a comparison of the figures in Table 4.8.3.1, above, with those in Table 4.3.1, earlier this chapter, it is apparent that, for every one of the six macroeconomic variables, the probability value has been made smaller by virtue of the extension. Previously, only one of the computed values of the F statistic was significant at the ten per cent level. Now, it is evident that four out of the six values are significant at the five per cent level. It is possible to infer that the real price of oil is responsible for Granger-causing not only LTIR but also PINF, TB and RW.

With reference to the block exogeneity test, in the context of the original linear VAR model, reference was made to the computed value of the chi-square statistic failing to exceed the corresponding ten per cent critical value. However, following the addition of W*Δlog.(ROILP) to the system, as has just been reported, a situation has been achieved where the computed value of the modified LR statistic comfortably surpasses the respective 0.5 per cent critical value.

Attention is now turned to whether or not evidence exists to support the real price of oil being Granger-caused by any of the six macroeconomic variables. In the context of the equation for Δlog.$(ROILP)_t$, in the extended VAR model, for each of j = 1, 2, ………, 6, an F test is performed of the null hypothesis,

Ho: $a_{7j,1} = 0$, $a_{7j,2} = 0$, $a_{7j,3} = 0$, $a_{7j,4} = 0$,

against the general alternative hypothesis,

Ha: at least one of $a_{7j,i} \neq 0$, (i = 1, 2, 3, 4).

The six computed values of the F(4, 94) statistic, together with the associated probability values, are displayed in Table 4.8.3.2, below.

Table 4.8.3.2: Results of Granger-Causality Tests with Δlog.(ROILP)$_t$ as the Dependent Variable

	Right-Hand-Side Variable		
	Δlog.(GDP)	Δlog.(REER)	Δlog.(RW)
F(4, 94) (probability value)	3.3231 (0.0136)	1.8413 (0.1274)	0.1702 (0.9531)
	Right-Hand-Side Variable		
	ΔPINF	ΔTB	ΔLTIR
F(4, 94) (probability value)	1.0829 (0.3695)	0.8040 (0.5256)	0.2293 (0.9213)

Estimation period: 1973q3-2005q1.

From a comparison of the table, above, with Table 4.3.2, in the third section of this chapter, it appears that the inclusion of W*Δlog.(ROILP) in the VAR system has brought about a fundamental change. Within the environment of the original linear VAR model, there was a lack of evidence to contradict the notion that the real price of oil is not Granger-caused by any of the six macroeconomic variables. Indeed, the lowest probability value (corresponding to Δlog.(REER)) was as high as 0.1898. Following the expansion of the model, however, there seems to be strong support for the argument that lagged values of output growth exert an influence upon the current value of Δlog.(ROILP). The probability value for the real effective exchange rate can be observed to fall to 0.1274, yet for none of the other four variables do the data come close to rejecting the null hypothesis at a conventional level of significance.[171]

[171] The inference that output growth Granger-causes the proportional change in the real price of oil would seem to be plausible if the business cycles for the major industrialised countries have been in synchronisation.

A more general F test is now conducted of the null hypothesis that none of the lagged values of any of the macroeconomic variables are responsible for determining the current value of Δlog.(ROILP). Hence, in relation to the equation for x_{7t} within the extended VAR model, the null hypothesis is

Ho: $a_{7j,1} = 0$, $a_{7j,2} = 0$, $a_{7j,3} = 0$, $a_{7j,4} = 0$, (j = 1, 2, ………, 6),

which is to be considered alongside the general alternative hypothesis,

Ha: at least one of $a_{7j,i} \neq 0$, (j = 1, 2, ……, 6; i = 1, 2, 3, 4).

The computed value of the $F(24, 94)$ statistic is 1.6859, which is associated with a probability value of 0.0400. Hence, at the five per cent level of significance, it is possible to reject Ho and to infer that past developments in the U.K. macroeconomy are of relevance for the current movement in the real price of oil. Hence, the adaptation of the linear VAR model has succeeded in reversing one of the earlier conclusions.

4.8.4 Impulse Response Functions and Forecast Error Variance Decompositions

In the context of the extended VAR model, consideration is now given to the estimated accumulated responses of the endogenous variables to a one standard deviation innovation in each of Δlog.(ROILP) and the weighted measure, W*Δlog.(ROILP). For the purpose of undertaking a Cholesky decomposition, it is necessary to specify an ordering of the endogenous variables (from most exogenous to least exogenous). The chosen sequence is: Δlog.(GDP); Δlog.(ROILP); W*Δlog.(ROILP); ΔPINF; ΔTB; ΔLTIR; Δlog.(RW); Δlog.(REER). The two sets of results are presented in Table 4.8.4.1 and Table 4.8.4.2, below.

Table 4.8.4.1: Estimated Accumulated Responses of Endogenous Variables to a One Standard Deviation Innovation in Δlog.(ROILP)

Quarters	Endogenous Variable			
	Δlog.(GDP)	Δlog.(ROILP)	W*Δlog.(ROILP)	ΔPINF
4	0.0001	0.1563	0.1076	0.2702
8	-0.0031	0.1371	0.0842	0.2346
12	-0.0040	0.1239	0.0823	0.1738
18	-0.0034	0.1263	0.0853	0.1602
24	-0.0033 (0.0019)	0.1275 (0.0254)	0.0851 (0.0231)	0.1700 (0.0668)

Quarters	Endogenous Variable			
	ΔTB	ΔLTIR	Δlog.(RW)	Δlog.(REER)
4	0.5767	0.4365	0.0009	0.0105
8	0.4146	0.4182	0.0018	0.0161
12	0.3075	0.3708	0.0018	0.0146
18	0.3117	0.3567	0.0013	0.0134
24	0.3206 (0.2130)	0.3645 (0.1351)	0.0014 (0.0025)	0.0137 (0.0082)

Analytic standard errors are contained in parentheses.
The sequence in which the variables are presented reflects the ordering which was chosen for the Cholesky decomposition.

Table 4.8.4.2: Estimated Accumulated Responses of Endogenous Variables to a One Standard Deviation Innovation in W*Δlog.(ROILP)

Quarters	Endogenous Variable			
	Δlog.(GDP)	Δlog.(ROILP)	W*Δlog.(ROILP)	ΔPINF
4	-0.0000	0.0197	0.0912	-0.2130
8	0.0010	0.0197	0.0844	-0.2391
12	0.0014	0.0252	0.0872	-0.2031
18	0.0009	0.0221	0.0844	-0.2080
24	0.0010 (0.0021)	0.0224 (0.0278)	0.0848 (0.0250)	-0.2127 (0.0737)

Quarters	Endogenous Variable			
	ΔTB	ΔLTIR	Δlog.(RW)	Δlog.(REER)
4	-0.2804	-0.3885	-0.0010	0.0103
8	0.0040	-0.2006	-0.0007	0.0031
12	-0.0123	-0.1918	-0.0007	0.0049
18	-0.0185	-0.1924	-0.0006	0.0051
24	-0.0182 (0.2409)	-0.1959 (0.1507)	-0.0007 (0.0028)	0.0049 (0.0092)

Analytic standard errors are contained in parentheses.
The sequence in which the variables are presented reflects the ordering which was chosen for the Cholesky decomposition.

On the basis of the figures which are contained in Table 4.8.4.1, with one exception, a disturbance to Δlog.(ROILP) prompts a movement in the same direction of all of the endogenous variables. The outlier is Δlog.(GDP), which can be seen to be negatively related to the oil price variable. For four out of the eight endogenous variables, the size of the ratio of the estimated accumulated response after twenty-four quarters to the associated standard error exceeds two. Additionally, in a further two cases, the magnitude is greater than 1.65. Indeed, only with respect to the future behaviour of Δlog.(RW), does an innovation in the oil price variable appear to be of negligible consequence. Where possible, when a comparison is performed of the estimates in the bottom rows of Table 4.8.4.1 and Table 4.4.1, it is evident that, in every instance, the addition of W*Δlog.(ROILP) to the analysis has succeeded in raising the significance of the estimated equilibrium effect of an unanticipated movement in Δlog.(ROILP).

An interpretation of the estimates which feature in the bottom row of Table 4.8.4.2 is that the occurrence of an increase in the U.K.'s exports of crude oil and/or a decrease in its consumption of this commodity, relative to its GDP, serves to dampen the consequence of a shock to Δlog.(ROILP) for each of Δlog.(GDP), ΔPINF, ΔTB, ΔLTIR and Δlog.(RW). In contrast, though, the positive reaction of Δlog.(REER) to an unexpected movement in Δlog.(ROILP) is seen to be enhanced. However, a comparison of the estimated accumulated responses with the respective standard errors reveals, for the six macroeconomic variables, a general lack of significance. Only in the case of ΔPINF is the absolute value of the ratio of the estimate to the standard error in excess of two.[172] Elsewhere, the largest absolute value is only 1.29 (corresponding to ΔLTIR).

Consideration is now given to the estimated accumulated responses of Δlog.(ROILP) after 4, 8, 12, 18 and 24 quarters to a one standard deviation in each of the endogenous variables.

[172] Specifically, the absolute value of the ratio is 2.88.

Table 4.8.4.3: Estimated Accumulated Responses of Δlog.(ROILP) to a One Standard Deviation Innovation in Each of the Endogenous Variables

Quarters	Endogenous Variable			
	Δlog.(GDP)	Δlog.(ROILP)	W*Δlog.(ROILP)	ΔPINF
4	-0.0601	0.1563	0.0197	-0.0331
8	-0.0246	0.1371	0.0197	-0.0390
12	-0.0265	0.1239	0.0252	-0.0261
18	-0.0316	0.1263	0.0221	-0.0252
24	-0.0309 (0.0305)	0.1275 (0.0254)	0.0224 (0.0278)	-0.0265 (0.0202)

Quarters	Endogenous Variable			
	ΔTB	ΔLTIR	Δlog.(RW)	Δlog.(REER)
4	0.0574	0.0235	0.0224	-0.0159
8	0.0307	0.0098	0.0254	-0.0265
12	0.0229	0.0121	0.0142	-0.0330
18	0.0256	0.0153	0.0126	-0.0319
24	0.0262 (0.0233)	0.0152 (0.0253)	0.0136 (0.0310)	-0.0309 (0.0320)

Analytic standard errors are contained in parentheses.
The sequence in which the variables are presented reflects the ordering which was chosen for the Cholesky decomposition.

The results which are displayed in Table 4.8.4.3, above, can be compared with those which were presented in Table 4.4.2, in the fourth section of this chapter. It appears that the signs of the estimated accumulated responses of Δlog.(ROILP) after twenty-four quarters to one standard deviation innovations in the six macroeconomic variables are unaffected by the addition to the VAR model of W*Δlog.(ROILP). Also, as before, in each of the six cases, the absolute value of the estimate fails to exceed two standard errors. Presented in relation to the standard error, the largest of the estimates is 1.31 (corresponding to ΔPINF), whereas, earlier, the maximum was 1.67 (corresponding to ΔTB).

In accordance with the methodology that was outlined in Chapter Three, the estimated version of the augmented linear VAR model is also used as a basis for undertaking forecast error variance decompositions. An attempt is made to ascribe the unexplained variation in an endogenous variable to shocks to both itself and the other seven variables entering the system. Reliance upon, in particular, a Cholesky decomposition requires the endogenous variables to be placed in order, from most to least exogenous. For the purpose of this exercise, the selected arrangement of the endogenous variables is exactly the same as when generating impulse responses.

Table 4.8.4.4: Forecast Error Variance Decompositions at the Twenty-Four Quarter Horizon

	Endogenous Variable			
Explained By → Variation In ↓	Δlog.(GDP)	Δlog.(ROILP)	W*Δlog.(ROILP)	ΔPINF
Δlog.(GDP)	74.083	5.2491	4.3604	0.9126
Δlog.(ROILP)	9.9286	65.067	9.3173	2.2472
W*Δlog.(ROILP)	1.6168	49.353	36.385	1.5043
ΔPINF	14.035	2.7940	8.7085	60.594
ΔTB	7.2400	6.1184	3.2280	3.4435
ΔLTIR	7.0156	10.650	12.941	7.2678
Δlog.(RW)	14.419	5.4172	3.2755	25.180
Δlog.(REER)	4.9653	3.0316	4.5320	4.5842

	Endogenous Variable			
Explained By → Variation In ↓	ΔTB	ΔLTIR	Δlog.(RW)	Δlog.(REER)
Δlog.(GDP)	3.5869	5.4743	2.5030	3.8303
Δlog.(ROILP)	5.4369	1.8857	1.0609	5.0569
W*Δlog.(ROILP)	1.0643	1.6246	2.1369	6.3145
ΔPINF	3.0759	2.7994	4.9372	3.0561
ΔTB	68.976	2.0680	5.1986	3.7276
ΔLTIR	17.605	38.797	4.4731	1.2500
Δlog.(RW)	5.2387	4.9937	37.015	4.4614
Δlog.(REER)	9.6422	10.324	2.9593	59.962

The figures which are presented in Table 4.8.4.4, above, indicate that Δlog.(ROILP) is relatively unimportant in terms of accounting for the variation in ΔPINF and Δlog.(REER). It can be seen that the variable fulfils a more prominent role in determining the behaviour of Δlog.(GDP), Δlog.(RW) and ΔTB. However, for only one of the macroeconomic variables (ΔLTIR) does the figure in the second column of the table exceed 10 per cent. In contrast, when the contributions of the two oil price variables, Δlog.(ROILP) and W*Δlog.(ROILP), are combined, all of the percentages are in excess of 7.5. Indeed, together, Δlog.(ROILP) and W*Δlog.(ROILP) assume responsibility for 11.5 and 23.6 per cent of the unexplained movement in ΔPINF and ΔLTIR, respectively.

4.8.5 Post-Sample Analysis

The same as in section 4.5 and sub-section 4.7.5 of this chapter, it is considered helpful initially to collect together values of statistics which summarise the goodness of fit over the within-sample period of the equations which comprise the estimated form of the extended VAR model.

Table 4.8.5.1: Summary of the Statistical Performance of the Estimated Equations Comprising the Extended Linear VAR Model

Dependent Variable	R-squared	S.E.	AIC	BIC
Δlog.(GDP)$_t$	0.3155	0.0084	-6.5035	-5.7645
Δlog.(ROILP)$_t$	0.3624	0.1545	-0.6786	0.0605
W*Δlog.(ROILP)$_t$	0.2757	0.1128	-1.3069	-0.5679
ΔPINF$_t$	0.5999	0.6612	2.2292	2.9683
ΔTB$_t$	0.3602	1.1405	3.3196	4.0587
ΔLTIR$_t$	0.4243	0.5751	1.9502	2.6893
Δlog.(RW)$_t$	0.4233	0.0104	-6.0726	-5.3335
Δlog.(REER)$_t$	0.3391	0.0334	-3.7403	-3.0012

Estimation period: 1973q3-2005q1.

For each of the seven original endogenous variables, it is possible to perform a comparison of the figures which are contained in Table 4.8.5.1, above, with the corresponding values which are presented in Table 4.5.1, in the first section of this chapter. The addition of W*Δlog.(ROILP) to the system and the accommodation of four lags on all of the variables have served to raise the value of the R-squared statistic in every case. The most marked increases correspond to ΔLTIR (0.2048) and Δlog.(ROILP) (0.1919). For each of ΔPINF, ΔTB and Δlog.(RW), the increment falls between 0.12 and 0.16. The most modest improvements are associated with Δlog.(GDP) and Δlog.(REER), equal to 0.0622 and 0.0900, respectively.[173]

When consideration is given to the respective values of the standard errors, it is discovered that, for all but one of the variables, the extension of the linear VAR model has succeeded in producing a reduction in size. The exception is Δlog.(GDP), for which a slender increase of 0.0001 is observed. The BIC, however, treats an overparameterised model more harshly, as evidenced by all seven of its values becoming greater, following the augmentation. Finally, concerning the AIC, it is noticeable that, in moving from the restricted to the unrestricted specification, in four instances, there occurs a fall in the value of the statistic.[174]

Attention now turns to the post-sample performance of the estimated version of the extended VAR model, which is assessed by computing, for seven of its equations, values of the mean square error, the mean error, the mean absolute error, the root mean square error and the median square error. The calculated values of these summary statistics are presented in Table 4.8.5.2, below.

[173] When performing comparisons, it should be recognised that, for the two VAR models, the estimation periods are not quite the same, as a consequence of admitting a greater number of lags on the endogenous variables to the extended system.

[174] Where possible, if a comparison is performed of the respective figures which are contained in Table 4.8.5.1 and Table 4.7.5.1 (corresponding to the asymmetric VAR model) then it is evident that, for all of the macroeconomic variables, with the exception of Δlog.(GDP), the value of the coefficient of determination is at least five percentage points higher in the former. Also, for four of the variables, the values of the standard error and the AIC are lower.

Table 4.8.5.2: Summary of the Post-Sample Performance of the Estimated Equations Comprising the Extended Linear VAR Model

Endogenous Variable	Mean Square Error	Mean Error (s.e)	Mean Absolute Error	Root Mean Square Error	Median Square Error
Δlog.(GDP)	0.98×10^{-5}	0.0013 (0.0009)	0.0025	0.0031	0.28×10^{-5}
Δlog.(ROILP)	0.0145	0.0391 (0.0343)	0.1069	0.1202	0.0140
ΔPINF	0.1231	-0.0065 (0.1058)	0.3004	0.3509	0.1188
ΔTB	0.2423	-0.0063 (0.1484)	0.3812	0.4922	0.1368
ΔLTIR	0.1119	-0.0155 (0.1008)	0.2964	0.3345	0.1095
Δlog.(RW)	0.56×10^{-4}	-0.0009 (0.0022)	0.0060	0.0075	0.24×10^{-4}
Δlog.(REER)	0.55×10^{-3}	-0.0092 (0.0065)	0.0196	0.0234	0.35×10^{-3}

Prediction period: 2005q2-2008q1.
Forecasts are based upon equations which have been estimated over a fixed period, 1973q3-2005q1.
s.e. denotes standard error of the sample mean, which is calculated by applying the square root operator to the ratio of the sample variance of a prediction error to the number of forecasts.

In the second numerical column of the table, there are shown values of the mean prediction error. The common sign of the first two of these values is indicative of a tendency for the values of Δlog.(GDP) and Δlog.(ROILP) to be underpredicted. For each of the remaining five variables, though, on average, the forecast exceeds the actual value. When the mean prediction error is divided by its standard error, for none of the endogenous variables does the absolute value of the ratio exceed 1.5. Indeed, in four cases, the size of the denominator is greater than that of the numerator. Additionally, for consumer price inflation and the two rates of interest, the value of the quotient is especially low. These findings are suggestive of the forecasts that are generated by the extended linear model being unbiased.

The values of the root mean square error which are listed in the fourth column of Table 4.8.5.2 are now viewed alongside the corresponding figures in the same column of Table 4.5.2, in the fifth section of this chapter. From a suitable comparison, it is possible to identify two circumstances in which the augmented equation is associated with a lower root mean square error and five situations in which it yields a higher value. This imbalance may encourage the conclusion to be reached that the empirical performance over the post-sample period of the VAR model which accommodates the additional variable, W*Δlog.(ROILP), is inferior to that of the linear VAR model. However, it should be respected that, in two cases, the degree of excess which is associated with the extended equation is less than two per cent. Prior to delivering a verdict on the relative capabilities of the two VAR models in terms of accounting for the post-sample data, then, it is recommended that formal statistical tests be applied.

The test of equality of forecast accuracy that was proposed by Harvey *et al*. (1997) allows an examination to be conducted of whether or not there exists a significant difference between corresponding values of the mean square forecast error. The null hypothesis assumes the form, Ho: $E[d_t] = 0$, where $d_t = e_{it}^2 - e_{jt}^2$, and, on this occasion, e_{it} and e_{jt} signify the prediction errors relating to the linear and extended specifications, respectively. For each of the seven variables which are common to the two VAR models, the computed value of the S_1^* statistic, which is required for the implementation of the test, is shown in Table 4.8.5.3.

Table 4.8.5.3: Computed Values of the S_1^* Statistic for the purpose of Testing for the Equality of the Forecast Accuracy of the Linear and Extended Linear VAR Models

	Endogenous Variable			
	Δlog.(GDP)	Δlog.(ROILP)	ΔPINF	ΔTB
Value of S_1^*	0.7907	-1.2466	0.9152	-1.1320

	Endogenous Variable		
	ΔLTIR	Δlog.(RW)	Δlog.(REER)
Value of S_1^*	-0.1789	-0.3340	-0.9998

Recall that the recommendation of Harvey *et al*. (1997) is to compare the computed value of the test statistic with a critical value that has been extracted from the table of the t distribution, corresponding to a number of degrees of freedom which equates with the number of forecasts less one. Hence, in this case, the relevant five and ten per cent critical values consist of 2.201 and 1.796, respectively. From an inspection of the computed values which are contained in the table, it is apparent that, in absolute terms, not one of these comes close to even the smaller of the two critical values. Hence, having conducted two-tailed tests at a conventional level of significance, it is not possible to infer that there is any difference in the forecasting accuracy of the two VAR models.

In conjunction with the two VAR systems, there is also the scope to investigate the hypothesis of forecast encompassing. On this occasion, however, because the linear model is nested within the extended model, for each of the seven endogenous variables, it is feasible to implement two different procedures. More specifically, there is the facility to perform not only the test that was favoured by Harvey *et al*. (1998) but also the test which was demonstrated to possess superior statistical properties, which is attributable to Clark and McCracken (2001).

Application of the encompassing test that was suggested by Harvey *et al*. (1998) again involves computing the value of the statistic, S_1^*. However, on this occasion, d_t, which enters the formula for the latter, is defined as $e_{it}(e_{it} - e_{jt})$, t = T+1, T+2, ……, T+n. If the objective is to assess whether or not the forecasts relating to the initial linear equation encompass those pertaining to the extended equation then the null hypothesis, Ho: $E[d_t] = 0$, should be contrasted with the one-sided alternative hypothesis, Ha: $E[d_t] > 0$.

Table 4.8.5.4: Computed Values of the S_1^* Statistic for the purpose of Testing for Forecast Encompassing in relation to the Linear and Extended Linear VAR Models

	Endogenous Variable			
	Δlog.(GDP)	Δlog.(ROILP)	ΔPINF	ΔTB
Value of S_1^*	1.2526	-0.9435	1.5075	-0.8896

	Endogenous Variable		
	ΔLTIR	Δlog.(RW)	Δlog.(REER)
Value of S_1^*	0.3360	0.1419	-0.5922

The computed values of the S_1^* statistic for seven endogenous variables are assembled in Table 4.8.5.4. The five and ten per cent critical values with which these should be compared are 1.796 and 1.363, respectively. From a study of the table, it is apparent that only one of the computed values exceeds either of the two critical values. Hence, at the ten per cent level of significance, it is possible to infer that the forecasts of ΔPINF which are produced by the linear model do not encompass the predictions which emanate from the less restricted equation. For all of the other variables, though, the information content of the forecasts which are generated by the augmented model cannot be regarded as superior to that of the predictions which are derived from the original specification.

In their 2001 paper, Clark and McCracken presented simulation results in order to support a proposal for applying a new test for forecast encompassing. They suggested, as a replacement for the statistic of Harvey *et al*. (1998):

$$ENC - NEW = n \frac{\frac{1}{n}\sum_{t=T+1}^{T+n} e_{it}\left(e_{it} - e_{jt}\right)}{\frac{1}{n}\sum_{t=T+1}^{T+n} e_{jt}^{2}}. \tag{3.7.7}$$

Critical values which are suitable for equations that have been estimated over a fixed interval are available in the not-for-publication appendix, which was produced by Clark and McCracken (2000).[175] Such values have been supplied for one hundred and thirty different combinations of π and k_2, where the former signifies the ratio of the number of forecasts (n) to the number of observations used in estimation (T), and the latter represents the additional number of regressors which enter the unrestricted specification.

[175] More specifically, the relevant source is Appendix Table 5 (p. 37).

Table 4.8.5.5: Computed Values of the ENC-NEW Statistic for the purpose of Testing for Forecast Encompassing in relation to the Linear and Extended Linear VAR Models

	Endogenous Variable			
	Δlog.(GDP)	Δlog.(ROILP)	ΔPINF	ΔTB
Value of ENC-NEW	0.9260	-0.8673	3.7952	-1.3652

	Endogenous Variable		
	ΔLTIR	Δlog.(RW)	Δlog.(REER)
Value of ENC-NEW	0.3763	0.0452	-0.4283

For each of seven endogenous variables, the computed value of the ENC-NEW test statistic is shown in Table 4.8.5.5, above. The asymptotic critical values which are provided by Clark and McCracken, which are the most suitable for the models which are subject to comparison in this section, correspond to $\pi = 0.1$ and $k_2 = 10$.[176] The estimates of the 90th, 95th and 99th percentiles of the relevant distribution consist of 1.252, 1.607 and 2.393, respectively.

By studying the figures in the table, it is evident that for only one of the endogenous variables does the computed value of the statistic exceed one of the percentiles. Consequently, the results which are obtained from application of the encompassing test that is favoured by Clark and McCracken reinforce the earlier finding that, only in relation to consumer price inflation, is the information content of the forecasts that are produced by the extended model superior to that of the predictions which emanate from the original linear specification.

[176] Critical values for $k_2 > 10$ and $\pi < 0.1$ are not available.

4.8.6 Results Relating to a Reduced Sample Period

The within- and post-sample analyses which have been performed have shown the linear VAR model largely to benefit from the introduction of the endogenous variable, W*Δlog.(ROILP). In particular, in every situation where a comparison was possible, the augmentation was seen to produce a sizeable increase in the value of the coefficient of determination. Also, with one exception, a decrease in the value of the standard error of the regression was achieved.[177]

For the two earlier VAR systems, estimation was additionally undertaken over the shorter interval, 1982q1-2005q1. For consistency, Table 4.8.6.1 shows values of summary statistics which are produced, having estimated the extended linear VAR model over the more restricted time period.

[177] It should be appreciated that the two VAR models were not estimated over exactly the same interval. Also, the two systems did not contain the same number of lags on the endogenous variables.

Table 4.8.6.1: Summary of the Statistical Performance of the Estimated Equations Comprising the Extended Linear VAR Model (Reduced Sample Period)

Dependent Variable	R-squared	S.E.	AIC	BIC
Δlog.(GDP)$_t$	0.4972	0.0047	-7.614	-6.7154
Δlog.(ROILP)$_t$	0.4197	0.1312	-0.9525	-0.0538
W*Δlog.(ROILP)$_t$	0.3943	0.1269	-1.0193	-0.1206
ΔPINF$_t$	0.6520	0.4518	1.5201	2.4188
ΔTB$_t$	0.3599	0.8596	2.8068	3.7055
ΔLTIR$_t$	0.3999	0.4622	1.5659	2.4645
Δlog.(RW)$_t$	0.4475	0.0062	-7.0526	-6.1540
Δlog.(REER)$_t$	0.4615	0.0304	-3.8775	-2.9788

Estimation period: 1982q1-2005q1.

Where possible, if a comparison is conducted of the corresponding figures which are contained in Table 4.8.6.1 and Table 4.6.7, it is apparent that, once again, in every case, the augmentation which has been applied has served to increase the value of the coefficient of determination by at least six percentage points. In particular, by virtue of having disregarded data prior to 1982, there becomes far more evident the gain to be derived from the extension in terms of explaining the variation in Δlog.(GDP).[178] In contrast, though, with respect to ΔPINF, the introduction of W*Δlog.(ROILP) into the analysis creates rather less of a positive impression than before. For Δlog.(GDP) and Δlog.(RW), the values of the standard error of the regression decrease as a result of the broadening the framework. However, in every instance, the values of the two information criteria happen to be lower for the original specification.[179]

[178] Also, by virtue of imposing a later start date, the advantage of a specification which includes Δlog.(ROILP) and W*Δlog.(ROILP) over one which houses SOPI and SOPD, becomes far clearer.

[179] It can be added that the extension that has been made to the linear VAR model has succeeded in achieving greater temporal stability. For three of the macroeconomic variables, little difference is observed in the values of the coefficient of determination corresponding to the estimation periods,

4.9 Empirical Analysis Performed in Conjunction with an Extended Version of the Asymmetric VAR Model

In sections 4.7 and 4.8 of this chapter, different responses have been witnessed to the observed deficiency of a linear VAR system for investigating the relationship between the price of oil and U.K. macroeconomic performance. One approach consisted of following Lee *et al*. (1995), by allowing for the effects of scaled, unanticipated increases and decreases in the real price of oil to be asymmetrical. The second strategy permitted the consequences of a development in the real price of oil to vary in accordance with the ratio of the U.K.'s exports to its consumption of crude oil. On the basis of the statistical evidence which has been presented, the decision to extend the original model by adding the weighted oil price measure, W*Δlog.(ROILP), appears to have been far more fruitful. However, the results from the second section should not be completely disregarded, which suggested that a separation of increases from decreases in the real price of oil serves to improve both the explanation of the data on ΔPINF over the within-sample period and the predictions of ΔLTIR from 2005q2 to 2008q1. Thus, it would seem appropriate, in a final section of this chapter, to examine the empirical performance of a VAR system which combines the distinctive features of the previous two models.

4.9.1 Statistical Properties of Additional Time Series

Consequently, a fourth VAR model is constructed by expanding the list of endogenous variables entering the earlier asymmetric system to include W*SOPI and

---

1973q3-2005q1 and 1982q1-2005q1. Also, in connection with the equations for $\Delta\log.(GDP)_t$ and $\Delta PINF_t$, reasons have been offered for a poorer fit of the data before 1982.

W*SOPD. The incorporation of these two extra variables in the model is designed to allow for a scaled unanticipated proportional rise/fall in the real price of oil to be of reduced (increased) influence, the greater (smaller) is the ratio of the U.K.'s exports to its consumption of crude oil. Prior to estimating the extended asymmetric VAR model, it is necessary to examine the stochastic properties of the time series on W*SOPI and W*SOPD. As before, both ADF and DF-GLS tests are applied in conjunction with the MAIC for determining the number of lags on the dependent variable in the test equation.[180] The results which are obtained from performing these tests are shown in Table 4.9.1.1 and Table 4.9.1.2.

Table 4.9.1.1: Results of Unit Root Tests Applied to W*SOPI

Unit Root Test		Deterministic Terms Allowed For In The Procedure
		Intercept/No Trend
ADF test		
Computed value of statistic		-2.3807
number of lags		11
probability value		0.1494
DF-GLS test		
Computed value of statistic		-1.4657
number of lags		11
10% critical value		-1.6149

[180] The series on W*SOPI and W*SOPD begin in 1973Q2. As before, for the purpose of undertaking a unit root test, data are not relied upon beyond 2005q1.

Table 4.9.1.2: Results of Unit Root Tests Applied to W*SOPD

Unit Root Test		Deterministic Terms Allowed For In The Procedure
		Intercept/No Trend
ADF test		
Computed value of statistic		-2.6703
number of lags		11
probability value		0.0823
DF-GLS test		
Computed value of statistic		-1.5108
number of lags		11
10% critical value		-1.6149

It can be seen that the unit root tests are conducted with an allowance for an intercept but not a linear trend term to enter the respective model. A study of the contents of the two tables reveals that, at the ten per cent level of significance, rejection of the null hypothesis is possible in only one case. However, the MAIC persistently deems there to be suitable as many as eleven lags on the dependent variable. In contrast, when analysing the series on W*SOPI, the implementation of a sequential testing procedure favours only one lag. Given this selection, the computed values of the ADF and DF-GLS statistics are -5.9898 and -5.3355, respectively. The former is associated with a probability value of 0.0000, while the latter is considerably less than the ten per cent critical value of -1.6150.[181]

[181] Given the manner of the construction of W*SOPI and W*SOPD, perhaps, the expectation would have been of no lags on the dependent variable being required in the respective test equation. With

The empirical evidence is consequently far from decisive concerning whether or not the series on W*SOPI and W*SOPD are stationary. However, it would seem to be somewhat incongruous to regard W*SOPI and W*SOPD as having different orders of integration, when the interpretation that was lent to SOPI and SOPD was the same. On balance, the statistical information which has been assembled is not considered to be sufficiently convincing to be dissuaded from the view that the processes which underpin the data on W*SOPI and W*SOPD do not contain a unit root. Thus, no transformation of the variables is undertaken, prior to assembling the VAR model.

4.9.2 Specification and Estimation of the Extended Asymmetric VAR Model

The extended asymmetric VAR model can be presented as the matrix equation:

$$x_t = A_0 + A_1 x_{t-1} + A_2 x_{t-2} + \cdots + A_p x_{t-p} + e_t. \qquad (3.6.2.3)$$

On this occasion, the system incorporates ten endogenous variables, the current values of which are located within the column vector, x_t. Also, A_0 indicates a column vector of constant terms, while A_i (i = 1, 2, ……, p) signify matrices of coefficients, each one of which is of order (10 x 10). Finally, the column vector, e_t, contains ten error terms which, in spite of not being subject to serial correlation, have the potential to be contemporaneously correlated, such that the off-diagonal elements of their variance-covariance matrix, Σ, need not all be equal to zero.

regard to both of the variables, when the ADF and DF-GLS tests are conducted prohibiting the admission of lags, in every situation, the data firmly reject the null hypothesis.

For the purpose of deciding upon the order of the VAR system, a maximum of four quarterly lags on the endogenous variables is imposed. Consideration is subsequently given to the values of the familiar three information criteria, together with the outcome of the implementation of a sequential testing procedure, involving, at each stage, computation of the value of the modified LR statistic. Relevant values are shown in Table 4.9.2.1.

Table 4.9.2.1: Values of the Modified LR Statistic and Information Criteria Corresponding to Different Orders of the Extended Asymmetric VAR Model

Order of VAR Model	LR Statistic	AIC	BIC	HQIC
0	N/A	-7.2339	**-7.0065**	-7.1415
1	349.90	**-8.7175**	-6.2157	**-7.7012**
2	147.03	-8.5321	-3.7558	-6.5918
3	137.61	-8.3988	-1.3481	-5.5347
4	**129.16**	-8.3421	0.9831	-4.5540

The bold font is used to signify the order of the VAR model which is favoured by the respective technique.

Regarding the figures which are displayed in Table 4.9.2.1, each of the VAR models has been estimated over a common sample period, extending from 1974q2 to 2005q1. Once again, the different selection methods are seen not to produce an identical outcome. According to the BIC, the decision to construct a VAR system at all is unmerited. However, the other two information criteria support the specification of a VAR(1) model, while the application of the sequential testing procedure results in the choice of p = 4. In this context, for the reason that overspecification is deemed to constitute less of a problem than underspecification, a preference is exhibited for including four lags on the endogenous variables in the VAR system.

4.9.3 Granger-Causality Tests

Having selected p to be equal to 4, the extended asymmetric VAR model can be presented as below.

$$
\begin{aligned}
x_{jt} = a_{j0} &+ a_{j1,1}x_{1,t-1} + a_{j1,2}x_{1,t-2} + a_{j1,3}x_{1,t-3} + a_{j1,4}x_{1,t-4} \\
&+ a_{j2,1}x_{2,t-1} + a_{j2,2}x_{2,t-2} + a_{j2,3}x_{2,t-3} + a_{j2,4}x_{2,t-4} \\
&+ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\
&+ a_{j10,1}x_{10,t-1} + a_{j10,2}x_{10,t-2} + a_{j10,3}x_{10,t-3} + a_{j10,4}x_{10,t-4} \\
&+ e_{jt},
\end{aligned}
\qquad (4.9.3.1)
$$

(j = 1, 2, ……, 10).

For convenience, x_1, x_2, ………, x_6 will be regarded as denoting the six macroeconomic variables, while x_7, x_8, x_9 and x_{10} correspond to SOPI, SOPD, W*SOPI and W*SOPD, respectively.

Having estimated each of the constituent equations using OLS, it is possible to conduct Granger-causality tests. The initial concern is with whether or not the current values of the macroeconomic variables are determined by past values of SOPI. Thus, for each j = 1, 2, ……, 6, an F test is performed of the null hypothesis,

Ho: $a_{j7,1} = 0$, $a_{j7,2} = 0$, $a_{j7,3} = 0$, $a_{j7,4} = 0$,

against the general alternative hypothesis, Ha: at least one of $a_{j7,i} \neq 0$, $(i = 1, 2, 3, 4)$.

Also, for the purpose of assessing whether or not lagged values of SOPD are informative with respect to the current values of the macroeconomic variables, for each $j = 1, 2, \ldots\ldots, 6$, an F test is conducted of the null hypothesis,

Ho: $a_{j8,1} = 0$, $a_{j8,2} = 0$, $a_{j8,3} = 0$, $a_{j8,4} = 0$,

against the alternative hypothesis,

Ha: at least one of $a_{j8,i} \neq 0$, $(i = 1, 2, 3, 4)$.

The results of these two sets of tests are displayed in Table 4.9.3.1.

Table 4.9.3.1: Results of Granger-Causality Tests Performed in Conjunction with Equation (4.9.3.1)

Oil Price Variable	Endogenous Variable		
	Δlog.(GDP)	Δlog.(REER)	Δlog.(RW)
SOPI	2.4301 (0.0540)	2.4142 (0.0553)	1.9844 (0.1044)
SOPD	0.4509 (0.7714)	1.5288 (0.2013)	0.8199 (0.5161)
	Endogenous Variable		
	ΔPINF	ΔTB	ΔLTIR
SOPI	8.0560 (0.0000)	2.8621 (0.0283)	4.1701 (0.0040)
SOPD	2.1122 (0.0865)	0.9797 (0.4232)	1.0173 (0.4033)

Estimation period: 1974q2-2005q1.
Computed values of the F(4, 83) statistic are shown in the cells. Associated probability values are contained in parentheses.

The most immediate conclusion to reach, having studied the contents of Table 4.9.3.1, is that an increase in the real price of oil has a greater influence on the macroeconomy than a decrease. In the rows which relate to SOPI, all but one of the computed values of the F statistics are significant at the ten per cent level. In contrast, in the rows that correspond to SOPD, only one of the probability values is seen to be less than 0.10.

It is of interest to perform a comparison of the figures which are contained in Table 4.9.3.1 with those which were reported in Table 4.8.3.1 in an earlier section of this chapter. It seems that, by virtue of separating rises from falls in the real price of oil, it has been possible to find evidence of a connection between movements in oil prices and the growth of GDP. Also, a significant relationship emerges between the behaviour of the price of oil and that of the exchange rate.

Having initially considered the six equations for the macroeconomic variables individually, the regression functions are now viewed collectively. More specifically, the objective is to perform three block exogeneity tests.

First, an assessment is formed of whether or not all of the coefficients which are attached to the lags on SOPI in the first six of the equations of the VAR model are equal to zero. In terms of mathematics, the validity of the null hypothesis,

Ho: $a_{j7,1} = 0$, $a_{j7,2} = 0$, $a_{j7,3} = 0$, $a_{j7,4} = 0$, (j = 1, 2, ..., 6),

is examined in comparison to the most general alternative hypothesis,

Ha: at least one of $a_{j7,i} \neq 0$, (j = 1, 2, ..., 6; i = 1, 2, 3, 4).

A similar test is conducted with respect to the lags on SOPD, such that the null and alternative hypotheses consist of:

Ho: $a_{j8,1} = 0$, $a_{j8,2} = 0$, $a_{j8,3} = 0$, $a_{j8,4} = 0$, (j = 1, 2, ..., 6); and

Ha: at least one of $a_{j8,i} \neq 0$, (j = 1, 2, ..., 6; i = 1, 2, 3, 4).

Finally, a more general system test is undertaken in order to investigate whether or not any of the lagged values of SOPI and SOPD are influential in explaining any of the current values of the six macroeconomic variables. Hence, on this occasion, the null and alternative hypotheses are specified as:

Ho: $a_{jk,1} = 0$, $a_{jk,2} = 0$, $a_{jk,3} = 0$, $a_{jk,4} = 0$, ($j = 1, 2, \ldots\ldots, 6$; $k = 7, 8$);

Ha: at least one of $a_{jk,i} \neq 0$, ($j = 1, 2, \ldots\ldots, 6$; $k = 7, 8$; $i = 1, 2, 3, 4$).

On account of restrictions being imposed upon parameters which enter six of the equations of the system, in each of the three cases, a modified form of LR test is performed. The three computed values of the test statistics are 87.9065, 42.3512 and 126.5277. For the first two tests, comparison should be made with a critical value that relates to a chi-square distribution which is associated with 24 degrees of freedom. However, for the most general test, the critical value should be drawn from the table of the chi-square distribution, corresponding to 48 degrees of freedom.

With respect to the first two tests, the five per cent critical value is 36.4. Thus, in both cases, the null hypothesis is comfortably rejected at a conventional level of significance. Concerning the final test, the five per cent critical value is 65.2, which is easily exceeded by the computed value of the statistic.[182] Hence, the results which are obtained from these tests confirm that lags on SOPI and SOPD should enter at least one of the equations for the six macroeconomic variables.

[182] This critical value has been achieved by linear interpolation, using the values for 40 and 50 degrees of freedom, 55.7585 and 67.5048, respectively.

The focus of attention now turns towards whether or not an oil price variable is Granger-caused by a macroeconomic variable. If the initial interest is in SOPI then, with reference to equation (4.9.3.1), above, for each of j = 1, 2, ……, 6, an F test is undertaken of the null hypothesis,

Ho: $a_{7j,1} = 0$, $a_{7j,2} = 0$, $a_{7j,3} = 0$, $a_{7j,4} = 0$,

against the alternative hypothesis,

Ha: at least one of $a_{7j,i} \neq 0$, (i = 1, 2, 3, 4).

When attention turns to SOPD, once again, in the context of equation (4.9.3.1), for each of j = 1, 2, ……, 6, an F test is performed in association with the null hypothesis,

Ho: $a_{8j,1} = 0$, $a_{8j,2} = 0$, $a_{8j,3} = 0$, $a_{8j,4} = 0$,

which is contrasted with the alternative hypothesis,

Ha: at least one of $a_{8j,i} \neq 0$, (i = 1, 2, 3, 4).

In connection with the twelve tests for Granger-causality, the computed values of the F statistics are indicated in Table 4.9.3.2.

Table 4.9.3.2: Results of Granger-Causality Tests with $SOPI_t$ and $SOPD_t$ as Dependent Variables

Oil Price Variable	Right-Hand-Side Variable		
	Δlog.(GDP)	Δlog.(REER)	Δlog.(RW)
SOPI	0.1838 (0.9462)	0.9547 (0.4369)	0.4401 (0.7793)
SOPD	1.4402 (0.2280)	1.5577 (0.1933)	1.2504 (0.2962)
	Right-Hand-Side Variable		
	ΔPINF	ΔTB	ΔLTIR
SOPI	0.2287 (0.9216)	0.4864 (0.7457)	0.3565 (0.8388)
SOPD	1.3486 (0.2589)	0.5336 (0.7114)	0.3777 (0.8240)

Estimation period: 1974q2-2005q1.
Computed values of the F(4, 83) statistic are shown in the cells. Associated probability values are contained in parentheses.

The figures which are contained in Table 4.9.3.2 demonstrate a general lack of influence of past values of the macroeconomic variables on the current values of SOPI and SOPD. It can be observed that, in every case, the probability value for SOPI is higher than that for SOPD. However, the lowest probability value still amounts to 0.1933. Consequently, at a conventional level of significance, it is not possible to reject any of the twelve null hypotheses that were specified above.

In conjunction with the equations for SOPI and SOPD, it is possible to conduct more general F tests. More specifically, for the purpose of assessing whether or not any of the past values of any of the six macroeconomic variables contributes towards the determination of the current value of SOPI, with reference to the equation for x_{7t} within the system (4.9.3.1), the null hypothesis, Ho: $a_{7j,1} = 0$, $a_{7j,2} = 0$, $a_{7j,3} = 0$, $a_{7j,4} = 0$, for all j = 1, 2, ……, 6,

is compared to the alternative hypothesis,

Ha: at least one of $a_{7j,i} \neq 0$, (j = 1, 2, ……, 6; i = 1, 2, 3, 4).

The computed value of the F(24, 83) statistic is 0.5547, which is associated with a probability value of 0.9483. Consequently, collectively, the lagged values of the macroeconomic variables account for only a negligible proportion of the variation in SOPI over the sample observations.

Similarly, in order to examine whether or not any of the past values of any of the macroeconomic variables exerts an influence over the current value of SOPD, in conjunction with the equation for x_{8t} within system (4.9.3.1), the null hypothesis,

Ho: $a_{8j,1} = 0$, $a_{8j,2} = 0$, $a_{8j,3} = 0$, $a_{8j,4} = 0$, for all j = 1, 2, ……, 6,

is considered alongside the alternative hypothesis,

Ha: at least one of $a_{8j,i} \neq 0$, (j = 1, 2, ……, 6; i = 1, 2, 3, 4).

In connection with this test, the computed value of the F(24, 83) statistic is 1.0912, which yields a probability value of 0.3717. Hence, although there seems to be a closer correspondence between scaled oil price decreases and earlier movements in macroeconomic variables, the computed value of the test statistic is far removed from being significant at a conventional level.

4.9.4 Impulse Responses and Forecast Error Variance Decompositions

As was the case with the three previous VAR models, the estimated form of the current system is solved for the purpose of generating impulse responses. In particular, Table 4.9.4.1 and Table 4.9.4.2, below, show the estimated accumulated effects on the ten endogenous variables of one standard deviation innovations in SOPI and W*SOPI, respectively.

Table 4.9.4.1: Estimated Accumulated Responses of Endogenous Variables to a One Standard Deviation Innovation in SOPI

Quarters	Endogenous Variable				
	Δlog.(GDP)	SOPI	SOPD	W*SOPI	W*SOPD
4	-0.0004	0.7067	0.2437	0.5730	0.2813
8	-0.0032	0.6634	0.2263	0.5247	0.2641
12	-0.0040	0.6712	0.1980	0.5279	0.2610
18	-0.0038	0.6527	0.2196	0.5035	0.2935
24	-0.0037 (0.0024)	0.6462 (0.1641)	0.2295 (0.1308)	0.4924 (0.1634)	0.3019 (0.1504)

(continued)

Quarters	Endogenous Variables				
	ΔPINF	ΔTB	ΔLTIR	Δlog.(RW)	Δlog.(REER)
4	0.1757	0.3141	0.1872	-0.0003	0.0125
8	0.0546	0.1291	0.1393	0.0002	0.0153
12	0.0690	0.0655	0.1600	0.0001	0.0126
18	0.0528	0.0459	0.1513	-0.0005	0.0114
24	0.0459 (0.0718)	0.0581 (0.2555)	0.1466 (0.1426)	-0.0006 (0.0031)	0.0117 (0.0093)

Analytic standard errors are contained in parentheses.
The sequence in which the variables are presented reflects the ordering which was chosen for the Cholesky decomposition.

Table 4.9.4.2: Estimated Accumulated Responses of Endogenous Variables to a One Standard Deviation Innovation in W*SOPI

Quarters	Endogenous Variables				
	Δlog.(GDP)	SOPI	SOPD	W*SOPI	W*SOPD
4	0.0004	0.0669	0.1073	0.2738	0.0709
8	0.0021	0.0689	0.1096	0.3222	0.0626
12	0.0026	0.0947	0.1104	0.3504	0.0519
18	0.0026	0.1020	0.1048	0.3663	0.0387
24	0.0025 (0.0020)	0.1072 (0.1347)	0.1000 (0.1044)	0.3750 (0.1335)	0.0339 (0.1210)

(continued)

Quarters	Endogenous Variables				
	ΔPINF	ΔTB	ΔLTIR	Δlog.(RW)	Δlog.(REER)
4	-0.0789	-0.2488	-0.0934	-0.0003	-0.0022
8	-0.0438	-0.1000	0.0449	0.0002	-0.0079
12	-0.0212	-0.1154	0.0053	-0.0000	-0.0060
18	-0.0155	-0.1016	0.0133	0.0002	-0.0058
24	-0.0153 (0.0616)	-0.1032 (0.2176)	0.0172 (0.1220)	0.0003 (0.0027)	-0.0059 (0.0080)

Analytic standard errors are contained in parentheses.
The sequence in which the variables are presented reflects the ordering which was chosen for the Cholesky decomposition.

A study of the figures which are contained in Table 4.9.4.1 and Table 4.9.4.2 enables certain observations to be made. First, it is evident that a given shock to SOPI stimulates a movement in the opposite direction of Δlog.(GDP) and Δlog.(RW), while the remaining macroeconomic variables follow the same broad path as the oil price variable. However, statistically, the calculated effects are seen to be weak. For three of the macroeconomic variables, the size of the estimate is less than that of the associated standard error. In absolute terms, the largest value of the ratio of the accumulated response to the standard error is only 1.54 (corresponding to Δlog.(GDP)).

It is apparent that, with respect to the six macroeconomic variables, with the exception of ΔLTIR, the estimates which feature in the bottom row of Table 4.9.4.2 have the reverse signs to those which enter the final row of Table 4.9.4.1. It would seem, then, that, in general, an increase in the U.K.'s exports of crude oil and/or a reduction in its consumption of this resource succeed in dampening the macroeconomic consequences of a disturbance to the real price of oil. However, with regard to the estimated effects after twenty-four quarters which feature in Table 4.9.4.2, there is only one instance in which the size of an accumulated response exceeds the value of the corresponding standard error. Still, for Δlog.(GDP), the value of the ratio of the former to the latter is only 1.25.

In Table 4.9.4.3 and Table 4.9.4.4, below, there are presented the estimated accumulated responses after twenty-four quarters of the endogenous variables to one standard deviation innovations in SOPD and W*SOPD, respectively.

Table 4.9.4.3: Estimated Accumulated Responses of Endogenous Variables to a One Standard Deviation Innovation in SOPD

Quarters	Endogenous Variable				
	Δlog.(GDP)	SOPI	SOPD	W*SOPI	W*SOPD
4	-0.0005	-0.1615	0.5975	-0.1702	0.5575
8	-0.0018	-0.1148	0.4472	-0.1897	0.4253
12	-0.0030	-0.0990	0.4389	-0.1853	0.4392
18	-0.0030	-0.1154	0.4509	-0.2052	0.4621
24	-0.0029 (0.0024)	-0.1266 (0.1623)	0.4592 (0.1296)	-0.2195 (0.1627)	0.4700 (0.1493)

(continued)

Quarters	Endogenous Variables				
	ΔPINF	ΔTB	ΔLTIR	Δlog.(RW)	Δlog.(REER)
4	-0.0981	0.4676	0.1384	-0.0017	0.0118
8	-0.0511	0.6540	0.2754	-0.0010	0.0111
12	-0.0918	0.4625	0.2147	-0.0012	0.0121
18	-0.0804	0.4625	0.2229	-0.0016	0.0104
24	-0.0828 (0.0731)	0.4720 (0.2598)	0.2198 (0.1443)	-0.0018 (0.0031)	0.0105 (0.0094)

Analytic standard errors are contained in parentheses.
The sequence in which the variables are presented reflects the ordering which was chosen for the Cholesky decomposition.

Table 4.9.4.4: Estimated Accumulated Responses of Endogenous Variables to a One Standard Deviation Innovation in W*SOPD

Quarters	Endogenous Variables				
	Δlog.(GDP)	SOPI	SOPD	W*SOPI	W*SOPD
4	0.0006	0.0416	0.0880	-0.0493	0.2450
8	-0.0005	0.0609	0.0985	-0.1077	0.2583
12	-0.0019	0.0356	0.0572	-0.1350	0.2336
18	-0.0020	0.0257	0.0570	-0.1520	0.2483
24	-0.0020 (0.0020)	0.0167 (0.1361)	0.0665 (0.1060)	-0.1649 (0.1329)	0.2586 (0.1221)

(continued)

Quarters	Endogenous Variables				
	ΔPINF	ΔTB	ΔLTIR	Δlog.(RW)	Δlog.(REER)
4	0.1531	0.2382	-0.0121	0.0034	0.0100
8	0.0847	0.4292	0.1209	0.0037	0.0128
12	0.0781	0.3342	0.1029	0.0035	0.0136
18	0.0606	0.3144	0.1028	0.0033	0.0121
24	0.0587 (0.0623)	0.3160 (0.2197)	0.0931 (0.1229)	0.0031 (0.0027)	0.0121 (0.0080)

Analytic standard errors are contained in parentheses.
The sequence in which the variables are presented reflects the ordering which was chosen for the Cholesky decomposition.

The figures which are contained in Table 4.9.4.3 show that a given shock to SOPD inspires a movement in the opposite direction of Δlog.(GDP), ΔPINF and Δlog.(RW), while the three remaining macroeconomic variables, ΔTB, ΔLTIR and Δlog.(REER), chart the same broad course as the oil price variable. In general, the macroeconomic indicators seem to react more strongly to an innovation in SOPD than to SOPI, as evidenced by there being only one instance of the value of a standard error exceeding the size of the corresponding estimate. The macroeconomic variable for which the magnitude of the accumulated response, relative to the value of the associated standard error, is the largest is ΔTB.[183]

The responses which are reported in Table 4.9.4.4 indicate a negative association between a shock to W*SOPD and the resultant behaviour of Δlog.(GDP), whereas a disturbance to the former encourages all of the other macroeconomic variables to move in the same direction. In the final row, it can be observed that four of the estimates relating to the macroeconomic variables are, in absolute terms, at least as

[183] The value of this ratio is calculated to be 1.82.

great as the respective standard errors. However, the maximum size of an accumulated response, compared to the value of its standard error, is only 1.51.[184] Thus, there would seem to be a general lack of significance surrounding the calculated effects.

The estimated version of the extended asymmetric VAR model is also used as a basis for undertaking decompositions of the variances of forecast errors, pertaining to twenty-four quarters in the future. In connection with explaining fluctuations in the endogenous variables, the assigned degrees of responsibility are shown in Table 4.9.4.5, below.

Table 4.9.4.5: Forecast Error Variance Decompositions at the Twenty-Four Quarter Horizon

	Endogenous Variable				
Explained By → Variation In ↓	Δlog.(GDP)	SOPI	SOPD	W*SOPI	W*SOPD
Δlog.(GDP)	66.436	4.9358	1.4436	1.4807	2.2894
SOPI	2.3609	78.193	4.4991	1.0025	1.7793
SOPD	4.1979	10.866	63.147	2.5342	3.8143
W*SOPI	2.8937	68.690	5.4315	10.229	2.7677
W*SOPD	3.7537	10.084	61.486	1.1621	8.6113
ΔPINF	14.078	5.1296	5.4675	4.6492	5.0573
ΔTB	5.8550	3.1398	8.2792	2.0999	5.2373
ΔLTIR	3.1413	5.7104	6.4086	7.6495	5.2429
Δlog.(RW)	8.1992	1.0664	3.0135	1.0585	5.9451
Δlog.(REER)	4.9495	5.3595	5.9364	3.3718	6.1985

(continued)

[184] The maximum corresponds to Δlog.(REER).

	Endogenous Variable				
Explained By → Variation In ↓	ΔPINF	ΔTB	ΔLTIR	Δlog.(RW)	Δlog.(REER)
Δlog.(GDP)	3.9884	6.5593	4.4748	3.3257	5.0563
SOPI	1.0595	3.7247	1.0617	3.5670	2.7528
SOPD	3.0052	1.5331	1.1287	3.9235	5.8502
W*SOPI	0.7979	1.5704	1.1193	3.9714	3.5298
W*SOPD	3.0490	1.6742	0.9606	3.0386	6.1802
ΔPINF	50.305	3.4477	4.1822	5.8390	1.8440
ΔTB	2.9083	60.710	2.0362	6.6231	3.1106
ΔLTIR	7.8547	17.421	37.932	5.9193	2.7210
Δlog.(RW)	26.483	5.1469	3.2980	43.444	2.3450
Δlog.(REER)	4.1773	5.9689	9.8214	5.2406	48.976

From a comparison of the percentages which are displayed in the second and third columns of Table 4.9.4.5, it would seem that SOPD is marginally more useful than SOPI in accounting for variations in the macroeconomic variables. It is evident that, only for Δlog.(GDP), is the figure in the second column greater than the number to its right. In terms of explaining the behaviour of the macroeconomic variables, the maximum responsibility which is assigned to SOPI is 5.7104. In contrast, though, for both of the rates of interest and the exchange rate index, SOPD is allocated a percentage which is in excess of 5.9.

It would seem that, collectively, SOPI and W*SOPI can take credit for 13.36 per cent of the unexplained movement in ΔLTIR, while the next highest figure is for ΔPINF (= 9.78 per cent). On the basis of the figures which are presented in the third and fifth columns of Table 4.9.4.5, at least 10.5 per cent of the variation in four of the macroeconomic variables can be attributed to SOPD and W*SOPD, combined.

However, when the relative influences of the four oil price variables are considered jointly, for three of the macroeconomic variables, ΔPINF, ΔLTIR and Δlog.(REER), a total of in excess of 20 per cent is achieved, while, for ΔTB, the sum contribution amounts to 18.76 per cent.

4.9.5 Post-Sample Analysis

It would seem that the extensions and adjustments that have been made to the initial VAR model have succeeded in attaching to the price of oil far greater prominence in terms of accounting for the macroeconomic performance of the U.K. since the early-1970s. However, a necessary condition for the results in this section to be viewed as credible is that the empirical performance of the associated VAR system be seen to be stable over time. As in earlier sections of this chapter, though, a review is firstly conducted of the ability of the estimated equations to explain the within-sample data on the ten endogenous variables.

Table 4.9.5.1: Summary of the Statistical Performance of the Estimated Equations Comprising the Extended Asymmetric VAR Model

Endogenous Variable	R-Squared	S.E.	AIC	BIC
Δlog.(GDP)	0.4684	0.0074	-6.7232	-5.7907
SOPI	0.2431	0.6281	2.1675	3.1000
SOPD	0.3485	0.5897	2.0416	2.9741
W*SOPI	0.2713	0.5171	1.7787	2.7112
W*SOPD	0.3042	0.5429	1.8760	2.8085
ΔPINF	0.6468	0.6421	2.2116	3.1441
ΔTB	0.3919	1.1181	3.3209	4.2534
ΔLTIR	0.5129	0.5401	1.8656	2.7981
Δlog.(RW)	0.4203	0.0100	-6.1061	-5.1736
Δlog.(REER)	0.3951	0.0333	-3.7050	-2.7724

Estimation Period: 1974q2-2005q1

Where possible, a comparison of the values of the statistics in Table 4.9.5.1, above, with those in Table 4.8.5.1, in the previous section, enables an assessment to be formed of the benefits which are derived from allowing for asymmetry in the context of a model which already permits the macroeconomic consequences of a change in the price of oil to vary in accordance with developments in the U.K.'s exports and consumption of crude oil. When examining corresponding values of the coefficient of determination, it is apparent that, for five out of the six macroeconomic variables, the value of the R-squared statistic which is indicated in Table 4.9.5.1 is larger. In particular, the explanation of the within-sample data on Δlog.(GDP) seems to prosper the most from accommodating the feature of asymmetry. For this variable, there occurs an increase in the value of the coefficient of determination which is in excess of 0.15. The other notable rise is 0.0886, which is associated with ΔLTIR.

In contrast to the coefficient of determination, the value of the standard error of the regression is computed, recognising the loss in the number of degrees of freedom that follows from OLS estimation. When comparing the respective figures that are listed in the second columns of Table 4.9.5.1, above, and Table 4.8.5.1, in the previous section, it is discovered that the entries in the former are smaller for all six of the macroeconomic variables. Concerning the values of the AIC, which are displayed in the third columns of the two tables, for four of the macroeconomic variables, an improvement is registered by allowing for asymmetrical effects of increases and decreases in the real price of oil. However, with regard to the values of the BIC, Δlog.(GDP) is the only variable for which a fall occurs.

Consideration is now given to the predictions which are generated over the interval, 2005q2–2008q1, by the equations which comprise the estimated version of the extended asymmetric VAR model. As per usual, for each endogenous variable, there are calculated values of the mean square error, the arithmetic mean error, the mean absolute error, the root mean square error and the median square error, all of which are shown in Table 4.9.5.2.[185]

[185] In fact, values of these statistics are not recorded for either W*SOPI or W*SOPD, on the basis that these variables are not incorporated in any earlier model, which thereby prevents comparisons from being undertaken.

Table 4.9.5.2: Summary of the Post-Sample Performance of the Estimated Equations Comprising the Extended Asymmetric VAR Model

Endogenous Variable	Mean Square Error	Mean Error (s.e)	Mean Absolute Error	Root Mean Square Error	Median Square Error
Δlog.(GDP)	0.69×10^{-5}	0.0011 (0.0007)	0.0019	0.0026	0.93×10^{-6}
SOPI	0.3084	0.1965 (0.1566)	0.4497	0.5553	0.1417
SOPD	0.1375	0.1275 (0.1050)	0.3332	0.3708	0.1064
ΔPINF	0.2758	-0.1036 (0.1552)	0.4271	0.5252	0.1977
ΔTB	0.3502	-0.0592 (0.1775)	0.4886	0.5917	0.1839
ΔLTIR	0.1311	-0.0256 (0.1089)	0.3041	0.3621	0.0602
Δlog.(RW)	0.47×10^{-4}	-0.0008 (0.0021)	0.0057	0.0069	0.24×10^{-4}
Δlog.(REER)	0.75×10^{-3}	0.0116 (0.0075)	0.0225	0.0273	0.41×10^{-3}

Prediction period: 2005q2-2008q1.
Forecasts are based upon equations which have been estimated over a fixed period, 1974q2-2005q1.
s.e. denotes standard error of the sample mean, which is calculated by applying the square root operator to the ratio of the sample variance of a prediction error to the number of forecasts.

From a study of the figures which are contained in the second numerical column of Table 4.9.5.2, it is apparent that, for Δlog.(GDP), Δlog.(REER) and the two oil price variables, there is a tendency for the respective equation to underpredict, while, for ΔPINF, ΔTB, ΔLTIR and Δlog.(RW), on average, the forecast exceeds the actual value. However, in four cases, the size of the mean prediction error is smaller than that of the associated standard error. Also, the largest absolute value of the mean, relative to its standard error, is only 1.5515 (corresponding to Δlog.(REER)), on the basis of which there would not seem to be an issue of bias.

In an attempt to assess whether or not the predictions emanating from the extended asymmetric VAR system are superior to those which were produced by the extended linear VAR model, relevant values of the root mean square error which are reported in the fourth column of Table 4.9.5.2 are contrasted with those which are contained in the same column of Table 4.8.5.2 in the preceding section of this chapter. From the comparison that is undertaken, it is evident that, for four of the macroeconomic variables, namely, ΔPINF, ΔTB, ΔLTIR and Δlog.(REER), the asymmetric model is associated with the larger root mean square error. Indeed, with respect to ΔTB, the extent of the increase is greater than twenty per cent, while, for ΔPINF, the surplus amounts to almost fifty per cent. For both Δlog.(GDP) and Δlog.(RW), in general, the accuracy of the forecasts seems to be enhanced by allowing for asymmetry. For these two variables, reductions in the value of the root mean square error are achieved of 16 and 8 per cent, respectively.

In conjunction with the two extended VAR models, formal tests for the equality of forecast accuracy will now be applied. In particular, for each of the six macroeconomic variables, the two-tailed test which was favoured by Harvey *et al*. (1997) will be performed, which requires construction of the null hypothesis, Ho: $E[d_t] = 0$, where $d_t = e_{it}^2 - e_{jt}^2$, and e_{it} and e_{jt} ($t = T+1, T+2, \ldots\ldots, T+n$) indicate the forecast errors corresponding to the extended linear and extended asymmetric equations, respectively. The implementation of the test demands the computation of the value of the statistic, S_1^*, which should be contrasted with a critical value which is extracted from the table of the t distribution, corresponding to n–1 (= 11) degrees of freedom. In connection with the six macroeconomic variables which are included in both of the VAR models, the computed values of S_1^* are shown in Table 4.9.5.3, below.

Table 4.9.5.3: Computed Values of the S_1^* Statistic for the purpose of Testing for the Equality of the Forecast Accuracy of the Extended Linear and Extended Asymmetric VAR Models

	Endogenous Variable		
	Δlog.(GDP)	ΔPINF	ΔTB
Value of S_1^*	1.1391	-1.6821	-1.6440

	Endogenous Variable		
	ΔLTIR	Δlog.(RW)	Δlog.(REER)
Value of S_1^*	-0.6569	0.6776	-1.3865

The signs of the computed values of the S_1^* statistic confirm the overall superiority of the extended linear VAR model in terms of predicting the values of four of the endogenous variables. In contrast, the extended asymmetric system produces generally more accurate forecasts of Δlog.(GDP) and Δlog.(RW). However, recalling that the relevant five and ten per cent critical values consist of 2.201 and 1.796, respectively, strictly, there is no significant difference in the quality of the predictions that are produced by the competing models for any of the six macroeconomic variables.

If an additional objective is to assess whether or not the forecasts which emanate from the extended asymmetric model possess no greater information content than those which are derived from the augmented linear model then there is available for application the forecast encompassing test of Harvey *et al.* (1998). The latter involves the construction of the null hypothesis, Ho: $E[d_t] = 0$, which is compared to the one-sided alternative hypothesis, Ha: $E[d_t] > 0$, where, on this occasion, $d_t = e_{it}(e_{it} – e_{jt})$. The implementation of this test procedure relies upon computation of the value of the statistic, S_1^*. For each of the six macroeconomic variables, the value of S_1^* is shown in Table 4.9.5.4.

Table 4.9.5.4: Computed Values of the S_1^* Statistic for the purpose of Testing for Forecast Encompassing in relation to the Extended Linear and Extended Asymmetric VAR Models

	Endogenous Variable		
	Δlog.(GDP)	ΔPINF	ΔTB
Value of S_1^*	1.8264	-1.3643	-1.1626

	Endogenous Variable		
	ΔLTIR	Δlog.(RW)	Δlog.(REER)
Value of S_1^*	-0.1967	0.9439	-0.6911

Harvey *et al.* (1998) recommend comparing the computed value of the test statistic with a critical value that has been extracted from the table of the t distribution, corresponding to n – 1 (= 11) degrees of freedom. For a one-tailed test, the relevant five and ten per cent critical values consist of 1.796 and 1.363, respectively. Upon observing the figures which are contained in the table, it is apparent that, for

Δlog.(GDP), it is possible to reject Ho at the five per cent level of significance. Hence, the inference can be drawn that the forecasts of output growth which are generated by the extended asymmetric model incorporate greater information. However, for the remaining variables, the computed value of S_1^* is seen not to exceed either of the two critical values.

4.9.6. Results Relating to a Reduced Sample Period

Once more, consideration is given to how well the respective VAR model fits the data over the reduced-length sample period, 1982q1-2005q1. More specifically, where possible, a comparison is conducted of the empirical performances of the corresponding equations entering the extended versions of the asymmetric and linear VAR systems. Table 4.9.6.1 shows, for the most recent VAR model, values of summary statistics which, for the six macroeconomic variables, can be contrasted with those which have been reported in Table 4.8.6.1.

Table 4.9.6.1: Summary of the Statistical Performance of the Estimated Equations Comprising the Extended Asymmetric VAR Model (Reduced Sample Period)

Endogenous Variable	R-Squared	S.E.	AIC	BIC
Δlog.(GDP)	0.5951	0.0045	-7.6587	-6.5421
SOPI	0.3552	0.6445	2.2597	3.3762
SOPD	0.5776	0.5478	1.9346	3.0511
W*SOPI	0.3678	0.5808	2.0515	3.1681
W*SOPD	0.5171	0.5504	1.9439	3.0605
ΔPINF	0.7222	0.4336	1.4671	2.5836
ΔTB	0.4020	0.8925	2.9108	4.0274
ΔLTIR	0.4668	0.4680	1.6197	2.7362
Δlog.(RW)	0.5352	0.0061	-7.0535	-5.9370
Δlog.(REER)	0.5324	0.0304	-3.8464	-2.7299

Estimation Period: 1982q1-2005q1

Recalling the results which corresponded to the full sample period, the greatest benefit to be derived from attaching the feature of asymmetry to the extended linear VAR model was seen to concern the ability to explain the variation in Δlog.(GDP). This broad result appears to remain undisturbed, having undertaken estimation over the shorter interval, on the basis that the value of the R-squared statistic increases by almost ten percentage points in progressing from the augmented linear to the extended asymmetric specification.

With regard to ΔPINF, ignoring the data prior to 1982 is found to raise slightly the degree of support for an asymmetric equation. The increment which is recorded in the value of the coefficient of determination is above seven percentage points when the sample period is restricted to 1982q1-2005q1, compared to approximately five percentage points when analysis is performed over the full period.

It would seem, though, that the most pronounced change which occurs from conducting estimation over the shorter time period concerns the real wage variable. For the full sample period, little difference could be observed between the two rival models in terms of either the value of the coefficient of determination or the value of the standard error of the regression. However, with respect to 1982q1-2005q1, in spite of there still being little to divide the values of the two standard errors, the value of the R-squared statistic for the extended asymmetric model now stands at nearly nine percentage points higher.[186]

4.10 Summary

In this final section of Chapter 4, an attempt is made to summarise the empirical results which have been obtained and to discuss their implications for the econometric modelling of the relationship between the price of oil and U.K. macroeconomic performance. For the purpose of undertaking empirical analysis, four different VAR systems were constructed and estimated. Two of these models were employed in the multi-country study by Jimenez-Rodriguez and Sanchez (2005). Also, it was recommended that each of these be extended to allow for the effects of a shock to the real price of oil to vary in accordance with fundamental structural changes which have occurred to the U.K. economy.

[186] It should be recognised that the extended version of the asymmetric model suffers from a lack of temporal stability. In connection with the macroeconomic variables, with the exception of for the two rate of interest variables, the reduction in the length of the sample period stimulates at least a seven percentage point increase in the value of the R-squared statistic.

The first system that formed the basis of analysis was a linear VAR model, which was estimated using quarterly data from 1973q2 to 2005q1. Having applied Granger-causality tests in conjunction with the latter, the evidence suggested, at best, only a weak association between movements in the real price of oil and macroeconomic performance. Additionally, not one of the estimated accumulated impulse responses (after twenty-four quarters) that was reported exceeded two standard errors. Having undertaken forecast error variance decompositions at the twenty-four quarter horizon, innovations in the real price of oil were seen to be capable of explaining almost ten per cent of the variation in the change in the long-term rate of interest. However, for the other five macroeconomic variables, the percentages ranged from 1.8 to 7.1.

When analysis was repeated over a shorter interval, 1982q1-2005q1, the broad finding of only a limited connection between the behaviour of the real price of oil and U.K. macroeconomic performance was not disturbed. However, there was apparent a general marked improvement in the fit of the data, which could not be attributed simply to the series on the endogenous variables being less erratic after 1981.

The second VAR model was formed by replacing the original oil price measure by volatility-adjusted increases and decreases in the real price of oil. On the basis of Granger-causality tests which were conducted over the interval, 1974q2-2005q1, there was evidence to suggest that past increases and decreases in the real price of oil contributed significantly towards the determination of (changes in) consumer price inflation, but none of the other macroeconomic variables. The accumulated impulse responses which were estimated indicated asymmetrical effects on the macroeconomic indicators of shocks to SOPI and SOPD. However, the only significant result to be obtained concerned the consequence for price inflation of an innovation in SOPI. The forecast error variance decompositions showed that collectively movements in the two oil price variables were capable of accounting for more than eleven per cent of the variation in both ΔPINF and ΔLTIR.

In terms of within-sample goodness of fit, the asymmetric VAR model did not seem to represent a distinct improvement upon the preceding linear VAR system. Also, mixed results were achieved from having undertaken a post-sample analysis over the interval, 2005q2-2008q1. The forecasts of ΔPINF and Δlog.(REER) that were produced by the linear model could be observed to be generally more accurate than those that were produced by the asymmetric system. However, not for all of the macroeconomic variables was it possible to draw the inference that the predictions that were derived from the linear VAR model encompassed those which were obtained from the asymmetric system.

From having performed estimation over the reduced-length sample period, 1982q1-2005q1, instability seemed to be as much a feature of the asymmetric model as it had been of the linear system. For three of the macroeconomic variables, the value of the R-squared statistic was enhanced by more than ten percentage points as a consequence of excluding from the analysis data prior to 1982. Also, from a comparison of values of the coefficient of determination corresponding to the linear and asymmetric specifications, there was discovered to be an absence of empirical support for modelling Δlog.(GDP) with increases and decreases in the real price of oil represented separately.

The third VAR model was created by adding to the linear system, as an endogenous variable, a weighted oil price measure. More specifically, the latter was formed by combining multiplicatively Δlog.(ROILP) and the ratio of the U.K.'s exports to its consumption of crude oil. Following estimation over the interval, 1973q3-2005q1, this augmentation was seen to have the consequence of raising the profile of the real price of oil in relation to the performance of the U.K. macroeconomy. For example, at the five per cent level of significance, it became possible to infer that four out of the six macroeconomic variables are Granger-caused by Δlog.(ROILP). Also, in absolute terms, estimates of the accumulated impulse responses of the macroeconomic variables to an innovation in Δlog.(ROILP) tended to surpass the values of the respective standard errors by a reasonable margin. Furthermore, the evidence suggested that either or both of an increase in the U.K.'s exports and a decrease in its consumption of crude oil (relative to G.D.P.) would serve to dampen the effect of a shock to the real price of oil on each of Δlog.(GDP), ΔPINF, ΔTB, ΔLTIR and Δlog.(RW). The forecast error variance decompositions which were undertaken indicated that collectively Δlog.(ROILP) and W*Δlog.(ROILP) are able to explain more than 7.5 per cent of the variation in all of the macroeconomic variables. Indeed, for ΔLTIR, the joint contribution exceeded twenty per cent.

The augmentation which was applied to the linear VAR model was seen, in general, to produce a substantial improvement in the fit of the within-sample data, as measured by the coefficient of determination. However, the superiority of the extended linear model was not quite as apparent over the post-sample period, 2005q2-2008q1. Nevertheless, in the case of ΔPINF, it was possible to conclude that the forecasts which emanated from the less restricted model possessed greater information content.

The problem of temporal instability was seemingly reduced, if not entirely eliminated, by virtue of including the variable, W*Δlog.(ROILP), in the analysis. For the majority of the endogenous variables, a superior fit of the sample data was achieved, having shortened the estimation period to 1982q1-2005q1. Only for Δlog.(GDP) and Δlog.(REER), though, was the differential of such a magnitude to be regarded as disconcerting. Furthermore, in the case of the former, meaningful comparisons are handicapped by the effect on output growth of the industrial action which occurred in the 1970s.

The final VAR system to provide the foundation for empirical analysis was an extension of the earlier asymmetric model. More specifically, two additional endogenous variables were created by multiplying each of SOPI and SOPD by the ratio of the U.K.'s exports to its consumption of crude oil.

Having estimated the augmented system over the interval, 1974q2-2005q1, and subsequently performed Granger-causality tests, it was evident that the introduction of the weighted measures helped to give emphasis to the asymmetric effects of increases and decreases in the real price of oil. Choosing the ten per cent level of significance, all but one (only one) of the macroeconomic variables could be inferred as being Granger-caused by SOPI (SOPD). There was a tendency for the estimated accumulated impulse responses to lack statistical significance. Indeed, on the basis of these results as well as the forecast error variance decompositions, it was not as clear that a rise in the real price of oil possessed more serious implications than a fall for macroeconomic performance.

From conducting a post-sample analysis, it was apparent that a significant benefit could be derived from allowing for the feature of asymmetry, when predicting future values of Δlog.(GDP). However, with respect to both ΔPINF and ΔTB, the quality of the forecasts seemed to deteriorate as a consequence of accommodating this characteristic. Also, from having estimated the final VAR model over the shorter interval, 1982q1-2005q1, as far as explaining the variation in output growth is concerned, the extended asymmetric specification was found to maintain a superiority over the augmented linear equation which had been estimated over the full data period.

In conclusion, the empirical evidence which has been presented in this chapter would seem to lend support to the key proposal that, in modelling the relationship between the price of oil and U.K. macroeconomic performance, fundamental changes to the U.K. economy should be recognised. Statistically, extending the linear VAR model to include the weighted oil price measure, W*Δlog.(ROILP), makes a greater impression than allowing for asymmetric effects of increases and decreases in the real price of oil. Additionally, the action that is taken of allowing W*SOPI and W*SOPD to accompany SOPI and SOPD in a non-linear VAR model helps to clarify the uneven consequences of positive and negative oil price shocks. In particular, without the recommended augmentation, the asymmetric nature of the behaviour of the growth of G.D.P. in the U.K. would not have been identified.

CHAPTER FIVE

METHODOLOGY: COINTEGRATION AND VECTOR ERROR-CORRECTION MODELLING

So far in this thesis, for the purpose of examining the relationship between the price of oil and U.K. macroeconomic performance, empirical analysis has been undertaken using the framework of an unrestricted VAR model. A virtue of operating in such a context is that associations which are established between the respective variables are largely determined by the data. The role played by economic theory has been limited to selecting the variables to enter the VAR system.[187] Another attractive feature is that the unrestricted VAR model has accommodated variables in a manner such that the corresponding time series are stationary. As a consequence, the results which have been achieved following estimation are less vulnerable to the criticism of most likely being spurious.

The practice of differencing a variable which has been identified as being integrated of order one would seem to be entirely reasonable when conducting a univariate analysis. However, in a multivariate environment, ignoring possible relationships which exist between variables in their original (levels) form runs the risk of a misspecification occurring. Also, a handicap may be suffered when confronted with the task of forecasting. Furthermore, by including in a system merely variables which are the outcome of first-differencing, only short-run behaviour is being characterised and the model is excluding information concerning the long run.

[187] Sometimes, economic theory provides the basis for the ordering of the variables that is required for a Cholesky decomposition. However, in the current study, recall that the ranking was chosen to accord with that which had been employed in a comparable econometric investigation by Jimenez-Rodriguez and Sanchez (2005).

From a statistical perspective, it is perfectly valid to feature in a system variables which have an order of integration of at least one, granted that they can combine to produce a stationary time series. A development of the unrestricted VAR model is the vector error-correction model (VECM). A desirable aspect of the latter is that, in addition to representing connections between endogenous variables pertaining to the short run, it incorporates any long-run, equilibrium relationships which have been verified.

5.1 The Relationship between a VAR Model and a VECM

This section commences by considering a standard VAR system of order p = 1 for the purpose of describing the inter-relationships which exist between n endogenous variables in their original (levels) form:

$$x_t = A_1 x_{t-1} + e_t. \qquad (5.1.1)$$

Regarding this equation, x represents an (n x 1) vector, containing values of the n endogenous variables, A_1 indicates a coefficient matrix of order (n x n), and e denotes an (n x 1) vector of stochastic disturbance terms. For convenience, deterministic terms have been excluded from the matrix equation.

A necessary and sufficient condition for the stability of the VAR system is that all of the eigen-values of A_1 have modulus of less than one. The eigen-values correspond to the roots of the characteristic equation, $|A_1 - \rho I_n| = 0$, where I_n constitutes an identity matrix which is of order (n x n). Alternatively, in the context of the reverse characteristic equation, $|I_n - \nu A_1| = 0$, the requirement is that all of the roots have modulus of greater than one.

The more general form of VAR system is the pth-order model, which is shown below:

$$x_t = A_1x_{t-1} + A_2x_{t-2} + \ldots\ldots\ldots + A_px_{t-p} + e_t. \tag{5.1.2}$$

With reference to the above system, A_i (i = 1, 2, ……, p) signify coefficient matrices which are of order (n x n).

The more general model can be expressed in its companion form as the first-order autoregressive process:

$$X_t = AX_{t-1} + E_t. \tag{5.1.3}$$

In connection with this specification, the following definitions apply: $X_t = (x_t, x_{t-1}, \ldots\ldots\ldots, x_{t-p+1})'$; $E_t = (e_t, 0, \ldots\ldots\ldots, 0)'$, which is of order (n·p x 1), where 0 symbolises a null vector which contains n elements;

$$A = \begin{bmatrix} A_1 & A_2 & \cdots & A_{p-1} & A_p \\ 0 & I_n & & 0 & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & 0 & \cdots & I_n & 0 \end{bmatrix}$$

Every element within A, above, is of order (n x n). Hence, the A matrix possesses $n \cdot p$ rows and columns. In order to satisfy the stability condition, the corresponding eigen-values must be less than one in absolute terms. Equivalently, the roots of the equation, $|I_{n \cdot p} - \nu A| = 0$, should have modulus of greater than one.

With respect to the standard VAR model, if it is ascertained that the n endogenous variables are integrated of order one (I(1)) then, out of a desire to achieve stability, a familiar response is to construct a system which contains the variables, expressed in the form of first-differences. However, it must be appreciated that it is possible to retain the variables in terms of levels, should there exist one or more linear combinations of these which are capable of generating a stationary time series. In a seminal paper, Engle and Granger (1987) maintained that, when n I(1) variables are 'cointegrated',[188] the VECM provides a valid characterisation of their short-run behaviour.[189]

The VECM which corresponds to equation (5.1.2) is presented below:

$$\Delta x_t = \alpha z_{t-1} + \Psi_2 \Delta x_{t-1} + \Psi_3 \Delta x_{t-2} + \dots\dots\dots + \Psi_p \Delta x_{t-p+1} + e_t. \qquad (5.1.4)$$

On the basis that r (> 0, < n) stationary time series can be obtained by forming suitable linear functions of the n endogenous variables then z constitutes a vector which is of order (r x 1). More specifically, z can be defined as $\beta' x_{t-1}$, where β fulfils

[188] The term, cointegration, can be regarded as referring to a situation in which a linear combination of variables, all of which have an order of integration of at least one is capable of producing a stationary time series. A more formal definition of this concept is provided in the paper by Engle and Granger (1987).
[189] This property forms part (4) of the Granger representation theorem (Engle and Granger (1987, p. 256)).

the role of an (n x r) matrix, the columns of which contain the parameters of the r cointegrating equations.[190] α represents an (n x r) matrix of adjustment coefficients, each column showing the responses of the endogenous variables to different types of disequilibrium. Finally, the (n x n) matrices, Ψ_i (i = 2, 3, ……, p), incorporate short-run coefficients.

Through substitution, the VECM can be written as:

$$\Delta x_t = \Psi x_{t-1} + \Psi_2 \Delta x_{t-1} + \Psi_3 \Delta x_{t-2} + \ldots\ldots\ldots + \Psi_p \Delta x_{t-p+1} + e_t, \qquad (5.1.5)$$

where $\Psi = \alpha\beta'$.

The coefficient matrices which feature in the equation, above, have a correspondence with those which are included in the VAR(p) model. Specifically:

$\Psi = -I_n + A_1 + A_2 + \ldots\ldots\ldots + A_p$; and

$\Psi_i = -(A_i + A_{i+1} + \ldots\ldots\ldots + A_p)$, $i = 2, \ldots\ldots\ldots, p$.

Consequently, the VECM can be considered to be a reparameterised version of the VAR model.

[190] The r columns of β are referred to as the cointegrating vectors. Also, the r cointegrating equations, $z = \beta' x$, have the interpretation of long-run relationships, with the elements of z indicating departures from equilibria.

5.2 Estimation of the VECM

Arising from the presentation of the VECM, there would appear to be two issues that need to be addressed. The first consists of how the number of cointegrating equations is established. The second concerns how the decomposition of Ψ between α and β is achieved. Single-equation approaches are available for the purpose of estimating α and β, and for conducting tests for cointegration. The most popular of these has been seen to be the two-step method of Engle and Granger (1987). However, a limitation of this type of procedure is that it is unable to cope with a situation in which there is more than a single equilibrium equation. Such a criticism does not apply when undertaking analysis in the context of a system of equations. The most widely adopted system technique is attributable to Johansen (1988, 1992). It must be respected that should the VAR model include n endogenous variables then, through following Johansen's recommendations, it is possible to detect the presence of as many as n-1 independent cointegrating equations.[191]

The first step in the implementation of the Johansen technique is to construct a standard VAR model which contains the relevant endogenous variables in the form of levels. This model is permitted to incorporate deterministic elements, such as a constant and linear trend term. A key consideration concerns the order of the VAR model, i.e., the maximum length of lag on the endogenous variables. It has been mentioned in the first methodological chapter in this thesis that there are available, for the purpose of deciding upon the lag structure of a VAR model, various information criteria. For example, following estimation, the econometric software

[191] It should be appreciated that the different cointegration analyses which have been proposed often fail to produce the same results. Pesavento (2004) has supplied a theoretical explanation for the superior performance of system methods over single-equation approaches.

package, *EViews*, supplies, upon request, values of the AIC, BIC and HQIC. An alternative strategy, having settled on the longest lag which is feasible, is to perform sequential LR tests in order to assess whether or not a lower order is acceptable.[192]

It has been demonstrated in the preceding empirical chapter of this thesis that a unanimous verdict is not always reached following the application of different selection methods. In connection with tests for cointegration, Lutkepohl and Saikkonen (1999) have confirmed that size distortion stems from an underspecification, while a loss of power results from the order of the model being too large. The findings which were obtained by Cheung and Lai (1993) from Monte Carlo simulations encourage the adoption of a cautious approach towards model specification. Having conducted twenty thousand replications in order to produce finite-sample critical values, in connection with Johansen's system tests for cointegration, Cheung and Lai witnessed that, compared to under-parameterisation, over-parameterisation was responsible for only a small degree of bias with respect to test size.[193,194]

Having decided upon the order, p, of the VAR model, the issue which next requires attention is how to produce estimates of the parameters of VECM. Johansen (1988, 1992) has advocated the implementation of a maximum likelihood approach, which will now be outlined.

[192] Additionally, it should be recognised that the selected model must be congruent with the data. Thus, a study of the residuals should reveal no evidence of autocorrelation or heteroskedasticity in the error terms. The residuals should also be seen not to refute the notion that the innovations are normally distributed.

[193] The specific experiment to which reference is being made assumed that data on the first-differences of two variables are generated by first-order autoregressive processes.

[194] In a relatively recent study, Emerson (2007) indicated the sensitivity of the cointegration results which are obtained from having employed the Johansen procedure to the number of lags which enter the underlying VAR model.

In the context of the VECM, the application of such a procedure consists of choosing values of the parameters, α, β, Ψ_2, Ψ_3, ……, Ψ_p, as well as the elements of the variance-covariance matrix of e_t (Σ), with the objective of maximising the value of the likelihood function. It should be respected that operating in conjunction with first-order conditions enables there to be obtained expressions for Ψ_2, Ψ_3, ……, Ψ_p in terms of α and β.

The residuals which are assembled following a regression of Δx_t on Δx_{t-1}, Δx_{t-2}, ……, Δx_{t-p+1} are contained within R_{0t}, which is of dimension (n x 1). Similarly, the residuals which are collected from a regression of x_{t-1} on Δx_{t-1}, Δx_{t-2}, ……, Δx_{t-p+1} are incorporated within R_{1t}, which is also an n-element column vector.

Residual product moment matrices can subsequently be formed from:

$$S_{ij} = \frac{1}{T}\sum_{t=1}^{T} R_{it}R'_{jt}, \quad (i, j = 0, 1). \tag{5.2.1}$$

Through controlling for or conditioning upon β, it is possible to produce an expression for the OLS estimator of α:

$$\alpha_{OLS} = S_{01}\beta[\beta' S_{11}\beta]^{-1}. \tag{5.2.2}$$

The estimator of the variance-covariance matrix of e_t depends upon α_{OLS} ($= S_{00} - \alpha_{OLS}\beta' S_{11}\beta\alpha_{OLS}'$). Through substituting for α_{OLS}, it is possible to express the estimator of Σ in terms of the solitary unknown, β ($= S_{00} - S_{01}\beta[\beta' S_{11}\beta]^{-1}\beta' S_{10}$).

Thus, excluding a constant, the (conditional) likelihood function, the value of which is being maximised, can be presented as:

$$L(\beta) = \left| S_{00} - S_{01}\beta[\beta' S_{11}\beta]^{-1}\beta' S_{10} \right| . \tag{5.2.3}$$

Johansen (1992) has shown that an estimate of β can be found by solving the eigen-value problem:

$$\left| \lambda S_{11} - (S_{10}S_{00}^{-1}S_{01}) \right| = 0.^{195} \tag{5.2.4}$$

The n solutions are signified by λ_1, λ_2, ……, λ_n, where the eigen-values have been ordered in accordance with size.[196] The eigen-vectors corresponding to the r largest roots combine to form the estimator of β. Having acquired estimators of the parameters of the cointegrating relationships, the expression for α_{OLS} (equation (5.2.2)) becomes operational.

5.3 Testing for Cointegration

Resulting from estimation, assuming the existence of r (> 0, < n) cointegrating vectors, the transformation of the likelihood value, $L^{-2/T}$, is a constant multiple of $\left| S_{00} \right| \prod_{i=1}^{r}(1 - \lambda_i)$. It should be respected that the largest possible number of equilibrium relationships is n (i.e., equal to the number of endogenous variables entering the VAR system). Given a desire to investigate whether or not the number

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[195] Equation (2.1) on p. 385 of the article by Johansen (1992).

[196] The eigen-values have the interpretation of the squared (canonical) correlation coefficients corresponding to R_{0t} and R_{1t}. It follows, then, that, in adopting the Johansen procedure, an attempt is being made to establish linear combinations of the variables in a levels form that are most strongly correlated with the variables in a first-differenced form.

of cointegrating equations exceeds r, there is the potential to perform an LR test. Application of the latter requires the computation of the value of the LR statistic:

$$-2log.L(H_r \backslash H_n) = -T\sum_{i=r+1}^{n} log.(1 - \lambda_i). \quad (5.3.1)$$

The above formulation is known as Johansen's trace statistic, and will subsequently be denoted by λ_{TRACE}. It is designed for the purpose of testing the null hypothesis, Ho: the number of cointegrating vectors $\leq$ r, against the alternative hypothesis, Ha: the number of cointegrating vectors > r.

The trace statistic does not possess a standard distribution. Hence, it is necessary to compare the computed value of λ_{TRACE} with a critical value which is the outcome of simulation experiments. The probability density function of the statistic is governed by the number of non-stationary components, (n–r), that are associated with the VAR model (according to Ho), as well as the deterministic terms which are present in the VECM. When applying a trace test, using the econometric software package, *EViews*, the default position is to rely upon critical values which have been produced by MacKinnon *et al*. (1999).

A test which possesses a similar foundation to, but a sharper focus than, the trace test is Johansen's maximum eigen-value test. In connection with the latter, the test statistic is defined as:

$$\lambda_{MAX} = -2log.L(H_r \backslash H_{r+1}) = -T\ log.(1 - \lambda_{r+1}), \quad (5.3.2)$$

which is suitable for testing the null hypothesis, Ho: the number of cointegrating vectors = r, against the specific alternative hypothesis, Ha: the number of cointegrating vectors = r+1. The distribution of λ_{MAX} is non-standard. Hence, in conducting the test, the computed value of the statistic is contrasted with a critical value which is the result of simulation experiments.[197]

It is appropriate to perform both the trace and maximum eigen-value tests in sequence. For example, with reference to the trace test, initially, r should be set to zero, and the validity of Ho: no cointegration should be compared with that of Ha: the number of cointegrating vectors > 0. If the null hypothesis cannot be rejected at a conventional level of significance then the exercise should immediately be halted, the inference being drawn that there is an absence of cointegration. The implication is that the matrix, Ψ, in the VECM has a rank of zero and, indeed, equates with a null matrix. In this situation, there is no gain to be made from specifying and estimating a VECM, rather than an unrestricted VAR model which contains the endogenous variables in the form of first-differences.

Conversely, if the null hypothesis is rejected then r should be upgraded by one, such that the trace test is being applied to Ho: the number of cointegrating vectors ≤ 1 against Ha: the number of cointegrating vectors > 1. If the computed value of λ_{TRACE} does not exceed the respective critical value then Ho cannot be rejected at the chosen level of significance. Strictly, the verdict which is necessarily reached is that the number of equilibrium relationships which can be assembled is equal to zero or one. However, given that sufficient evidence has already been found to be able to refute

[197] In the empirical analysis which follows, again, critical values are relied upon which have been generated by MacKinnon *et al*. (1999).

the notion that there is no cointegration, by virtue of elimination, one cointegrating vector is deemed to be relevant.

A rejection of Ho, above, demands that the procedure continues by allowing the data to decide between Ho: the number of cointegrating vectors ≤ 2 and Ha: the number of cointegrating vectors > 2. In general, the acceptance of a null hypothesis, Ho: the number of cointegrating vectors $\leq r^*$, requires the analysis to be terminated, whereas rejection compels a progression towards testing Ho: the number of cointegrating vectors $\leq r^*+1$. In a situation of persistent rejection of the constructed null hypotheses, the final test that would be administered considers the merits of Ho: the number of cointegrating vectors $\leq n-1$, in the company of Ha: the number of cointegrating vectors = n. Should the outcome of the final application of the trace test favour Ha, the suggestion is that Ψ possesses full rank (n), which will only be the case when all of the series on the endogenous variables, in their levels form, are stationary. Hence, in this extreme circumstance, the specification of a VECM is not justified. Instead, the foundation of the empirical investigation should be the unrestricted VAR model which was presented towards the beginning of this chapter, namely, matrix equation (5.1.2).

In connection with the maximum eigen-value test, the sequence begins by performing a comparison of Ho: no cointegration and Ha: the number of cointegrating vectors = 1. A failure to be able to reject Ho at a conventional level of significance demands an end to the procedure. Otherwise, the suitability of Ho: the number of cointegrating vectors = 1 is assessed alongside Ha: the number of cointegrating vectors = 2. Again, a situation in which the computed value of λ_{MAX} is no greater than the corresponding critical value necessitates a conclusion to the operation. Otherwise, there is assembled a new null hypothesis, Ho: the number of cointegrating vectors = 2, which is to be contrasted with Ha: the number of cointegrating vectors = 3.

In general, no subsequent tests are conducted once the data have exhibited a preference for Ho: the number of cointegrating vectors = r* over Ha: the number of cointegrating vectors = r*+1. However, in the case of repeated rejection of null hypotheses, the final test would be applied to Ho: the number of cointegrating vectors = n-1. Granted that the accompanying alternative hypothesis consists of Ha: the number of cointegrating vectors = n, it is apparent that, in their final stages of implementation, the maximum eigen-value and trace tests are identical.

It should be understood that, when performing sequentially the two different Johansen tests for cointegration, the same inference is not guaranteed. Based upon this recognition, an obvious question to pose is which of the trace and maximum eigen-value tests is the more reliable? Lutkepohl *et al*. (2001) examined the small-sample properties of the two tests. An observation which was made was that, while the trace test is sometimes poorer with respect to size, the maximum eigen-value test frequently suffers from a lack of power.

As part of an earlier study, Cheung and Lai (1993) investigated the sensitivity of the Johansen tests to the error terms in the respective system not being normally distributed. In relation to the probability density functions of the innovations, it was discovered that the degree of skewness significantly affected the size of both the trace and the maximum eigen-value tests. In contrast, though, the size of the trace test was found to be more robust than that of the λ_{MAX} test to a variation in excess kurtosis.

With respect to both of the Johansen tests, Cheung and Lai detected a problem in relying upon asymptotic critical values, when analysis is undertaken in the context of a finite sample. More specifically, the results of their Monte Carlo experiments showed that, in this situation, the trace and maximum eigen-value tests are biased towards rejection of the null hypothesis. The bias appeared to be a positive function of both the dimension and the order of the VAR system. This result encouraged the recommendation to transform the critical values, employing as a multiple, $T/(T - n \cdot p)$. Equivalently, Reimers (1992) suggested using the inverse of the latter for the purpose of scaling down the computed values of the statistics.[198]

Perhaps, a cautious approach towards determining the number of cointegrating vectors (r) consists of sequentially performing both trace and maximum eigen-value tests (applying the aforementioned correction factor). The accepted number of equilibrium relationships would correspond to the maximum that arises from the implementation of the two procedures, on condition that each long-run equation can be provided with an economic interpretation. In an attempt to receive verification that all of the linear combinations of the endogenous variables succeed in producing stationary series, an inspection is conducted of the time plots of $\beta_i' x_t$ and $\beta_i' R_{1t}$, i = 1, 2, ……, r, where β_i incorporates the estimates of the elements which comprise the ith cointegrating vector.

[198] The proposed adjustments, in fact, originate from a paper by Reinsel and Ahn (1988).

5.4 Simultaneous Determination of the Order of the VAR Model and the Cointegrating Rank

For the purpose of satisfying the objective of determining the number of cointegrating relationships, the approach which has been suggested appears to involve two steps. First, a decision is taken with respect to the optimal length of lag on the endogenous variables. Second, with the order of the VAR model having been imposed, analysis proceeds by performing Johansen's trace and maximum eigen-value tests. As an alternative to adopting a sequential strategy, though, there is the potential to select the order of the VAR model (p) and the cointegrating rank (r) simultaneously. More specifically, for each of a number of different combinations of values of p and r, the value of an information criterion could be calculated. The relevant number of equilibrium relationships would then correspond to the value of r that contributes towards the minimum value that is achieved of the information criterion.

It would seem that fundamental to the implementation of this alternative method is the choice of an information criterion. In this respect, it is, once again, helpful to make reference to the studies by Reimers (1992) and Cheung and Lai (1993). Reimers conducted simulation experiments for the purpose of comparing the performances of the AIC, BIC and HQIC. In conjunction with a true model for which $p = 1$ and $r = 0$, the Schwarz criterion was found to be the most successful in identifying correctly the order and rank. In contrast, though, the attainment level of the AIC was discovered to be very poor.[199]

Through the use of Monte Carlo experiments, Cheung and Lai (1993) were able to contrast the empirical and nominal sizes of cointegration tests under different circumstances. Initially, they employed as a framework a model in which the first-differences of two variables are described by stationary first-order autoregressive processes. Selecting the order of the VAR model in accordance with either the AIC or BIC, the empirical size of the test was seen to be greater than its nominal size by only a slender margin.[200] However, when the data on the first-differences of the variables were underpinned by first-order moving average processes, irrespective of the criterion which was adopted, the empirical size exceeded considerably the nominal size.

5.5 The Inclusion of Deterministic Terms in the VECM

An important matter which has yet to be addressed in this chapter is the incorporation of deterministic terms in the VECM. More specifically, consideration should be given to the issue of whether the system should feature a constant and/or linear trend term. Recalling the VECM which was presented earlier (equation (5.1.5)), the element, $\beta' x_{t-1}$, represents the r long-run equilibrium relationships and is sometimes referred to as the 'cointegration space'. In contrast, the component which is beyond $\alpha\beta' x_{t-1}$, on the right-hand side of the matrix equation, has received the

[199] In other contexts, e.g., p = 2, r = 2, the ability to form the appropriate judgement appeared to be governed by the strength of the cointegration.
[200] In this situation, results showed the BIC to be more successful in choosing the correct lag length. Nevertheless, the AIC reached the correct verdict on 99.86 per cent of occasions.

description of the ‘data space’. It is possible for a constant and a linear trend term to enter both of these two sectors. However, if it is accepted that the appearance of a given deterministic term in the cointegration space precedes its presence in the data space, and that the inclusion of an intercept term commands priority over that of a linear trend term, in either environment, then there is the scope for five categories of VECM.

Model 1: No constant term or linear trend term in either the cointegration space or the data space.

Model 2: A constant term in the cointegration space, but not the data space. No linear trend term in either the cointegration space or the data space.

Model 3: A constant term in both the cointegration space and the data space. No linear trend term in either the cointegration space or the data space.

Model 4: A constant term in both the cointegration space and the data space. A linear trend term in the cointegration space, but not the data space.

Model 5: A constant term and linear trend term in both the cointegration space and the data space.

Specification of Model 3, above, would seem to create an identification problem. Consequently, an explanation is required of how it is possible to distinguish between the numerical contributions of the two constant terms which are located in the different areas of the VECM.

The solitary constant term which enters the corresponding unrestricted VAR model is denoted by μ, which is an (n x 1) column vector. For the purpose of decomposing this into two unrelated parts, $\alpha_\perp$ is introduced, which represents a matrix of order (n x (n-r)) that has the property of being orthogonal to α, such that $\alpha'\alpha_\perp = 0$. Additionally, μ_1 indicates the (r x 1) vector of constant terms which are admitted to the cointegration space, while μ_2 signifies the ((n-r) x 1) vector of constant terms which are accommodated within the data space of the VECM.

On the basis of the various definitions which have just been provided:

$$\mu = \alpha\mu_1 + \alpha_\perp\mu_2. \tag{5.5.1}$$

Premultiplication by $(\alpha'\alpha)^{-1}\alpha'$ enables the expression for μ_1 to be achieved:

$$\mu_1 = (\alpha'\alpha)^{-1}\alpha'\mu. \tag{5.5.2}$$

Similarly, following pre-multiplication by $(\alpha_\perp'\alpha_\perp)^{-1}\alpha_\perp'$, there emerges the result:

$$\mu_2 = (\alpha_\perp'\alpha_\perp)^{-1}\alpha_\perp'\mu.\text{[201]} \tag{5.5.3}$$

With reference to Model 5, it should be respected that an analogous approach can be adopted in order to achieve a partitioning of the single linear trend term, which features in the unrestricted VAR model, into two unconnected elements. However,

[201] Concerning the distribution of μ between the cointegration and data spaces, the strategy which is adopted by *EViews* is to allocate to a long-run equation an intercept term which forces the error-correction term to have a mean of zero.

the relevant analysis will not be shown for the reason that Model 5 constitutes an unusual choice of class of VECM.

It was mentioned earlier that the probability distributions of Johansen's test statistics, λ_{TRACE} and λ_{MAX}, are dependent upon the dimension of the non-cointegration space, (n-r), and the deterministic terms which are included in the VECM. Consequently, a failure to utilise the appropriate framework for the empirical investigation incurs the risk of drawing erroneous inferences about the number of equilibrium relationships.[202] A pertinent issue, then, concerns how to choose between the five models which are available to the researcher.

The following points are intended to serve as guidance concerning the specification of the VECM:

- If the series corresponding to the endogenous variables in the form of levels do not exhibit a linear trend then the constant term should be restricted to entering the cointegration space. The presence of a constant term within an equilibrium equation removes the constraint of the associated relationship being compelled to pass through the origin.

- If the original series contain linear trends which are not regarded as cancelling out one another then a trend term should be located within the cointegration space.

[202] More specifically, the study by Gonzalo and Lee (1998) has indicated that if the chosen model does not allow for trending behaviour when this is visible in the data then there will often occur spurious rejection of the null hypothesis.

- The presence of an intercept term in the data space allows for a constant rate of change of the endogenous variables in the form of levels. Furthermore, the additional inclusion of a trend term in this segment of the model permits the possibility of quadratic trends in the data.

- Economic theory may be used as an aid to selecting the appropriate framework. For example, it may be considered that price inflation is related to the deviation of G.D.P. from its trend path, which would suggest accommodating a deterministic trend in the cointegration space (as in the empirical study by Hendry and Mizon (1993)).

- In practice, the two extreme classes of VECM tend not to be selected. Thus, usually, the decision is between models 2, 3 and 4.

If there is a desire to minimise the extent of discretion that is employed in econometric modelling and testing then there is available a procedure which was suggested by Hansen and Juselius (1995) for the purpose of jointly establishing the cointegrating rank and category of VECM. Hansen and Juselius advocated an application of the Dickey-Pantula principle (Dickey and Pantula (1987); Pantula (1989)), which involves an ordered progression from the most to the least restrictive framework, concluding the exercise on the first occasion on which a null hypothesis cannot be rejected at a conventional level of significance.

Table 5.5.1: Framework for the Application of the Dickey-Pantula Procedure

Null Hypothesis	Type of VECM				
	Model 1	Model 2	Model 3	Model 4	Model 5
Ho: r = 0					
Ho: r ≤ 1					
Ho: r ≤ 2					
………					
………					
Ho: r ≤ n-1					

With reference to the table which has been constructed, above, the starting point would be the top left-hand corner, with a test being performed of Ho: r = 0 in the context of Model 1. A rejection of the null hypothesis would necessitate a movement rightwards along the first row, such that the same null hypothesis is examined within the environment of Model 2. From the outset, given five straight rejections, attention would turn to the validity of Ho: r ≤ 1, having adopted Model 1 as a framework for analysis.

Thus, it is apparent that the path which is being followed consists of left to right, top to bottom. The testing sequence continues until either the data permit the acceptance of a null hypothesis or 5n consecutive rejections have occurred. In practice, what are regarded as implausible scenarios are sometimes removed. Indeed, in some empirical studies, it is found that consideration is restricted to merely models 3 and 4.[203,204]

[203] For example, see Table 15.27 (p. 692) within Patterson (2000).

[204] When applying the Dickey-Pantula principle, the Monte Carlo results of Hjelm and Johansson (2005) need to be respected, which reveal a distinct bias towards choosing Model 3, when the data-generating process is, in fact, Model 4.

5.6 Identification of the Long-Run Cointegrating Equations

It is assumed that, following the sequential application of trace and maximum eigen-value tests, the inference is drawn that there are r (> 0, < n) cointegrating vectors. If r = 1 then the cointegrating vector is unique, and so no consideration need be given to resolving an identification problem. In contrast, though, if r > 1 then restrictions are required on the parameters of the cointegrating vectors in order to be able to distinguish between the equilibrium relationships.

A necessary condition for the identification of a cointegrating equation is that its parameters be subject to at least r–1 independent restrictions. This is sometimes referred to as the 'counting' or 'order' condition. Most commonly, these restrictions involve setting the values of parameters equal to zero, thereby effectively excluding the associated variables from the respective equation. Also, on occasions, the values of two parameters are constrained to be of the same size. For example, on the basis of Purchasing Power Parity theory, within an equation that has been constructed to describe the logarithm of the exchange rate, the values of the parameters which are attached to the logarithms of the domestic and foreign price levels are required to be equal, but opposite in sign.

Satisfying the order condition is, on its own, insufficient for achieving identification. Hence, more definitively, if the matrix, β, is regarded as being comprised of the r column vectors, β_1, β_2, ……, β_r, each one of which contains n elements, then identification of β_j occurs when it is impossible to form a linear combination from the remaining r–1 vectors which is restricted in the same manner as β_j. It follows that if the controls which are applied to a set of r cointegrating vectors entail each of the equilibrium relationships including a variable which is unique then the respective equations have to be identified.

Although the type of econometric modelling which is favoured in this thesis is largely data driven, it is accepted that the restrictions which are imposed upon the parameters of the long-run equations should be motivated by economic principles. Garratt *et al*. (2003) have made the seemingly extreme recommendation that a formal, *ex ante*, theoretical analysis should underpin the structural, equilibrium relationships.[205] However, economic theory may not always be capable of delivering the desired degree of precision. Also, if the estimate of a parameter is observed to be insignificantly different from zero then, regardless of the prediction of the theory, it would appear to be entirely reasonable to remove the corresponding variable from the relevant equation, should such a response serve to aid the attainment of identification.

5.7 Testing the Validity of Restrictions on Long-Run Parameters

The assumption is made that the sufficient conditions are satisfied to enable the identification of r cointegrating vectors. Additionally, if it is supposed that the long-run equations are 'overidentified' then it is possible to assess the validity of the restrictions which have been imposed by performing a standard chi-square test.

[205] For the purpose of producing long-run relationships which could be contrasted with the data, Garratt *et al*. (2003) relied upon: accounting identities which connected flow to stock variables; assumptions concerning the determination of output; arbitrage conditions; and solvency requirements.

Recall that the matrix, β, incorporates the parameters of the r cointegrating equations. In order to achieve exact identification, the application of r–1 restrictions is required on each of the r columns of β. Thus, in total, the necessary number of constraints is equal to r(r–1). It follows, then, that, in the case of exact identification, the number of freely estimated long-run parameters amounts to rn – r(r–1).

In a situation of overidentification, the number of freely estimated parameters falls below rn – r(r–1). Consequently, if s_i is used to denote the number of parameters within the ith column of β for which the sample data are permitted to produce estimates then, when there is overidentification, $\sum_{i=1}^{r} s_i <$ rn – r(r–1). Also, the number of overidentifying restrictions, ν, can be calculated by subtracting the left-hand side from the right-hand side of the inequality, i.e., $\nu = rn - r(r-1) - \sum_{i=1}^{r} s_i = r(n - r + 1) - \sum_{i=1}^{r} s_i$.

It is possible to reach a verdict concerning the suitability of the restrictions which are imposed on the parameters of the long-run equations by undertaking a comparison of eigen-values. A more formal explanation can be provided by recollecting the representation of the r largest eigen-values resulting from an unconstrained cointegration analysis: $\lambda_1, \lambda_2, \ldots\ldots\ldots, \lambda_r$. The matching eigen-values which arise from the same form of empirical exercise, but having applied restrictions to the elements of β, are denoted by: $\lambda_1^*, \lambda_2^*, \ldots\ldots\ldots, \lambda_r^*$. It should be respected that the size of canonical correlation coefficient cannot be enhanced by the enforcement of a constraint. However, if the restriction is not binding then there will be no discrepancy between λ_i and λ_i^* (i = 1, 2, ………, r). On this basis, the relative magnitude of the statistic,

$$T\sum_{i=1}^{r}[log.(1 - \lambda_i^*) - log.(1 - \lambda_i)],$$

can be employed to determine whether or not the restrictions are valid.

More precisely, it is appropriate to contrast the computed value of the above statistic with a critical value which is extracted from the table of the chi-square distribution, corresponding to ν degrees of freedom and a conventional level of significance. Should the computed value of the statistic fail to exceed the critical value then the evidence is considered insufficient to be able to refute the notion that the restrictions are valid. Otherwise, the sample data are construed as not lending support to the constraints which have been applied to the long-run equations.

Finally, in the context of assessing the validity of restrictions on the long-run parameters of a model, it must be understood that an inability to reject a null hypothesis does not necessitate its acceptance. The possibility exists of assembling other sets of restrictions which also do not suffer the fate of being contradicted by the data. Hence, additionally, the restrictions should give rise to equations to which meaningful economic interpretations can be attached. Furthermore, the resultant estimates of the adjustment coefficients must be considered to be plausible.

5.8 Restricting Values of Adjustment Coefficients and the Concept of Weak Exogeneity

It should be respected that an approach which is identical to that which has just been described in relation to the matrix, β, can be implemented for the purpose of testing the validity of restrictions which are placed on the adjustment coefficients within the VECM.[206,207] In connection with the latter, though, the type of null hypothesis which is generally of interest asserts that all of the r elements in a given row of α are equal to zero. On the basis that the jth row is of interest, then, according to the null hypothesis, the jth endogenous variable (x_j) fails to respond to any of the r different forms of disequilibrium. In such a situation, x_j is referred to as being 'weakly exogenous', with reference to the parameters in β and the remaining (n–1)r adjustment coefficients within α.[208]

Having performed the appropriate chi-square test, should it be inferred that x_j is weakly exogenous then the original VECM can be partitioned into conditional (or partial) and marginal systems. The conditional model is created from the original specifications for Δx_{it} ($i = 1, 2, \ldots\ldots, n; i \neq j$), which are augmented by the inclusion of Δx_{jt} as a regressor. The marginal model is comprised of purely the equation for Δx_{jt}, which, of course, now omits all of the r disequilibrium terms.[209]

It should be respected that, having reduced the size of the VECM by conditioning, the same estimates of the parameters of the long-run equations and the adjustment coefficients are achieved as when analysis is undertaken in conjunction with the original model, with the weak exogeneity restrictions imposed. However, the

[206] In this context, the chi-square distribution is associated with a number of degrees of freedom which are equal to the number of restrictions which are applied to the elements of α.
[207] Similar to when performing the Johansen tests of cointegration rank, the suggestion has been made that a degrees of freedom correction be applied to the test statistic. Indeed, Psaradakis (1994) showed how such a simple modification serves to improve the properties of LR tests when conducting an analysis which is founded upon a small sample.
[208] If, additionally, there is no linear dependence of Δx_{jt} on past values of Δx_i ($i = 1, 2, \ldots\ldots, n; i \neq j$) then x_j can be described as 'strongly exogenous'. A distinction is made between different degrees of exogeneity in the paper by Engle *et al*. (1983).
[209] The original VECM is an example of a 'closed' system, for there is an attempt to explain the behaviour of all of the variables which enter the model. In contrast, if the number of variables exceeds the number of equations which form a system then the latter is described as 'open'.

asymptotic distributions of Johansen's cointegration rank statistics will have altered. Note that Pesaran *et al*. (2000) have generated critical values which are suitable for use when the equilibrium relationships incorporate between zero and five exogenous I(1) variables.

5.9 The Parsimonious VECM and the Structural VECM

This section commences by assuming that a cointegration analysis has been performed. Additionally, it is maintained that sufficient restrictions have been imposed upon the parameters of the long-run equations to achieve identification, and that these have been supported by the data. Moreover, chi-square tests for weak exogeneity have been undertaken.

On the basis that the existence of r (> 0, < n) equilibrium relationships has been inferred, the following closed, reduced-form VECM can be constructed:

$$\Delta x_t = \alpha\beta' x_{t-1} + \Psi_2 \Delta x_{t-1} + \Psi_3 \Delta x_{t-2} + \ldots\ldots\ldots + \Psi_p \Delta x_{t-p+1} + e_t. \quad (5.9.1)$$

The matrix, β, is of order (n x r), and strictly contains estimates of the parameters of the long-run equations. Also, α denotes an (n x r) matrix of adjustment coefficients. For convenience, the model has been shown not to incorporate any deterministic terms. Furthermore, it is accepted that the design of the model guarantees congruency with the data.[210]

[210] If a model is congruent with the data then, from routine diagnostic tests which are conducted, there should be a lack of evidence to suggest that the error terms are autocorrelated, heteroskedastic or fail to comply with a normal distribution.

If the r columns of β are formed from the (n x 1) vectors, β_1, β_2, ..., β_r, then the disequilibrium terms can be represented by $z_{t-1} = (\beta_1'x_{t-1}, \beta_2'x_{t-1}, ..., \beta_r'x_{t-1})'$, which is of order (r x 1). Thus, the VECM can equivalently be expressed as:

$$\Delta x_t = \alpha z_{t-1} + \Psi_2 \Delta x_{t-1} + \Psi_3 \Delta x_{t-2} + \ldots\ldots\ldots + \Psi_p \Delta x_{t-p+1} + e_t. \qquad (5.9.2)$$

Granted that the same variables appear on the right-hand side of each of the n equations which comprise the system then OLS yields efficient estimates. Furthermore, for the reason that every one of the variables is associated with a stationary time series, standard F and t tests, relating to the parameters of an equation, are valid.

Within this environment, predictions can be generated of the values of the dependent variables, for comparison with the forecasts which have been produced by the earlier unrestricted VAR models. Also, there is the possibility of performing Granger-causality tests. However, it needs to be respected that, within a short-run model which incorporates long-run, cointegrating relationships, a different interpretation of Granger-causality is required to earlier in this thesis. Specifically, in order for the variable, x_i, to be classed as not Granger-causing the variable, x_j, within the equation for Δx_{jt}, not only should all of the parameters which are attached to lags on Δx_i but also all of the adjustment coefficients must be equal to zero. Consequently, the pronouncement that x_j is not Granger-caused by x_i (or, indeed, any of the other n–2 variables within the VECM), necessitates the former complying with the characteristics of a weakly exogenous variable.

Operating at the level of the individual equations, F tests can be legitimately undertaken in an attempt to confirm the weak exogeneity of the relevant variables. Having reached the conclusion that n_1 variables possess this property, where $0 < n_1 < n$, it is possible to proceed towards constructing a conditional VECM:

$$\Delta x^{+}_{t} = \boldsymbol{\alpha}^{+} z_{t-1} + \Psi_0^{+}\Delta w_t + \Psi_2^{+}\Delta x_{t-1} + \Psi_3^{+}\Delta x_{t-2} + \ldots\ldots\ldots \qquad (5.9.3)$$
$$+ \Psi_p^{+}\Delta x_{t-p+1} + e_t.$$

With reference to the above matrix equation, Δx^{+}_{t} denotes a column vector which houses $n–n_1$ elements, each one of which represents the current value of the first-difference of an originally perceived endogenous variable which has subsequently not been inferred as being weakly exogenous. On the right-hand side, α^{+} constitutes a matrix of adjustment coefficients of order $((n–n_1) \times r)$. Δw_t signifies an $(n_1 \times 1)$ vector of the first-differences of the current values of the weakly exogenous variables. Finally, Ψ_0^{+} and Ψ_i^{+} $(i = 2, 3, \ldots\ldots, p)$ constitute matrices of short-run coefficients. However, in order to be compatible with the vectors to which they are connected, Ψ_0^{+} is of order $((n–n_1) \times n_1)$, while the remainder are comprised of $(n–n_1)$ rows and n columns.

Following OLS estimation, an effort is made to reduce the size of the model, as measured by the number of parameters, by performing statistical tests. More specifically, consideration is given to whether or not the data support the exclusion of a one or more of the right-hand-side variables from all $(n–n_1)$ of the equations. Consequently, at this stage, a desire is still being conveyed for the equations of the VECM to contain a common set of regressors. The model which is obtained, given that this is of a smaller magnitude, is referred to as the 'parsimonious' (conditional) VECM.[211]

Having achieved the parsimonious VECM, progression is made towards the development of the 'structural' VECM. The latter permits the $(n–n_1)$ endogenous variables to be contemporaneously related. Thus, the structural VECM extends the conditional VECM by permitting the entry of, into each of its equations, as regressors, the current values of the other endogenous variables in the system. The model which is created is shown below:

$$\Phi\Delta x^{+}_{t} \;=\; az_{t-1} \;+\; \Psi_0^{++}\Delta w_t + \;\Psi_2^{++}\Delta x_{t-1} \;+\; \Psi_3^{++}\Delta x_{t-2} \;+\; \ldots\ldots\ldots \qquad (5.9.4)$$
$$+\; \Psi_p^{++}\Delta x_{t-p+1} \;+\; \zeta_t.$$

Regarding the above equation, Φ indicates a square matrix of order $((n–n_1)$ x $(n–n_1))$, for which the off-diagonal elements are not constrained to being equal to zero. On the right-hand side, *a* represents a matrix of error-correction coefficients, and is of order $((n–n_1)$ x r). The matrices, Ψ_0^{++} and Ψ_i^{++} (i = 2, 3, ……, p), incorporate short-run parameters. These matrices include a common number of rows, $(n–n_1)$, yet Ψ_0^{++} contains only n_1 columns, compared to n for each of Ψ_i^{++} (i = 2, 3, ……, p). Finally, the column vector, ζ_t, accommodates $(n–n_1)$ stochastic error terms.

The relationships between the components of the structural and conditional models are clarified below:

[211] It should be respected that, in order for the parsimonious model to be viewed as acceptable, from having implemented well-established diagnostic checks, the system must be seen to be congruent with the data.

$$\alpha^{+} = \Phi^{-1}a; \tag{5.9.5}$$
$$\Psi_i^{+} = \Phi^{-1}\Psi_i^{++} \text{ (i = 0 and i = 2, 3, …… , p)}; \tag{5.9.6}$$
$$\varepsilon_t = \Phi^{-1}\zeta_t. \tag{5.9.7}$$

Given that every equation which is accommodated within the structural VECM possesses the same broad composition then an identification problem exists. Equations can be made observationally distinguishable by imposing restrictions on the short-run structure of the model.[212] Identification of an equation is achieved should it not be possible to create this from a linear combination of the remaining $[(n–n_1)–1]$ equations in the system. Thus, identification is guaranteed when every equation features at least one unique predetermined variable.

When an equation is identified and its parameters are subject to $[(n–n_1)–1]$ restrictions, the equation can be pronounced as being 'exactly identified'. In contrast, should the number of restrictions exceed $[(n–n_1)–1]$, the descriptive term, 'overidentified', is applicable. In contrast to when addressing the issue of the identification of the long-run, cointegrating equations, the source of the constraints which are imposed on the short-run structure of the VECM tends to be the statistical information that is contained in the sample data, rather than economic theory.

Unless Φ is a diagonal matrix then a system method, such as Full Information Maximum Likelihood, or Three-Stage Least Squares is required to estimate the parameters of the structural VECM. Statistical testing will determine the composition of the short-run relationship for each of the endogenous variables. When all of the terms have been removed from the system which are empirically of no relevance, the

[212] The short-run structure includes the elements of the variance-covariance matrix of ζ_t.

end result is a model which can be referred to as (the estimated form of) the 'parsimonious' structural VECM. The estimated version of the parsimonious structural VECM, in combination with that of the corresponding marginal model, may be regarded as the most appropriate framework to rely upon for the purpose of drawing inferences about the relationship between the price of oil and U.K. macroeconomic performance.

5.10 Summary

In Chapter Four, analysis was performed in conjunction with an unrestricted VAR model, out of a willingness to minimise the input of economic theory towards establishing relationships between the price of oil and the U.K. macroeconomy. Such a model can be considered desirable from a statistical perspective, granted that variables enter the system in a form such that the associated time series are stationary. Additionally, the model should include sufficient lags for disturbance terms to be non-autocorrelated.

A criticism which can be directed towards an unrestricted VAR model, though, is that it provides a representation of purely short-run behaviour and fails to allow for the existence of stable long-run, i.e., cointegrating, relationships between the respective variables. In the presence of cointegration, short-term developments are suitably described by an error-correction model. This type of a framework permits variables to respond systematically to situations of long-run disequilibria.

The methodology which has been presented earlier in Chapter Five has indicated a procedure for achieving an appropriate VECM. Central to this methodology is an assessment of whether or not cointegrating equations can be formed from the variables entering the analysis. Soren Johansen (1988, 1992) has proposed tests which have been extensively adopted in empirical research. In conducting either a trace test or a maximum eigen-value test, fundamental decisions have to be taken, such as the order of the underlying VAR model and the deterministic terms to be included in the cointegration and data spaces of the VECM. It must also be respected that the same inference need not be drawn from the application of the alternative tests and that the use of a finite-sample correction could alter substantially the verdict that is reached.

Having come to a decision concerning the number of cointegrating vectors, the corresponding VECM can be constructed and estimated. A general policy is advocated of undertaking exclusion tests with the objective of acquiring a parsimonious representation of the data. If one of the endogenous variables is inferred as not being dependent upon any of the disequilibrium terms then it can be pronounced as being weakly exogenous. As a consequence, the single VECM can be partitioned into conditional and marginal models.

The conditional model is comprised of equations for the remaining endogenous variables which include on their right-hand sides, *inter alia*, current values of the weakly exogenous variables. In contrast, the marginal model is assembled from equations for the weakly exogenous variables which incorporate only lagged values of variables as regressors.[213] Ultimately, an allowance is made for contemporaneous relationships between the endogenous variables.. This gives rise to the structural form of the VECM, which should be estimated by a system method, such as Full Information Maximum Likelihood or Three-Stage Least Squares. It is on the basis of the estimated versions of the structural and marginal models that final conclusions should be reached.

[213] In this context, Ordinary Least Squares is a valid form of estimation.

CHAPTER SIX

EMPIRICAL ANALYSIS PERFORMED IN CONJUNCTION WITH A RESTRICTED VAR MODEL

6.1 Cointegration Analysis

The purpose of this chapter is to implement the methodology that has been outlined in Chapter Five, which culminates in the estimation of a parsimonious structural VECM. The first step is the construction and estimation of an unrestricted VAR model, containing the endogenous variables in the form of levels. The selection of type of VAR model is governed by the econometric results which were obtained from the earlier analyses involving I(0) variables. In particular, influencing the choice is the marked improvement in empirical performance which was observed, having allowed for the macroeconomic effects of a change in the real price of oil to be connected to the U.K.'s consumption and exports of crude oil. Consequently, the decision is taken to admit to the system the variables: log.(GDP); log.(ROILP); W*log.(ROILP); PINF; TB; LTIR; log.(RW); log.(REER). Additionally, the model includes the deterministic terms, a constant and a linear time trend.[214]

Quarterly, seasonally-adjusted data are available on all of the variables from 1972q3 to 2008q1. The same as in earlier empirical chapters, observations from 2005q2 to 2008q1 are retained for evaluating the predictive capabilities of the equations of a model. Consequently, in estimation, data are not relied upon beyond 2005q1. The

[214] In adopting this framework, it should be respected that the possibility of asymmetric effects of increases and decreases in the price of oil is being denied in the long run.

time trend assumes a start value of 1 (in 1972q3) and increases by one unit on each occasion of moving forward by one quarter.

Utilising a common sample period, which extends from 1973q4 to 2005q1, the unrestricted VAR(p) model is estimated for values of p which are equal to 0, 1, 2, 3, 4 and 5.[215] The corresponding values of the AIC, the BIC and the HQIC are shown in the table below. The table also indicates, for each of the orders of VAR model from 1 to 5, the computed value of the modified LR test statistic.

Table 6.1.1: Values of the Modified LR Statistic and Information Criteria Corresponding to Different Orders of the Unrestricted VAR Model

Order of VAR Model	LR Statistic	AIC	BIC	HQIC
0	NA	-1.0395	-0.6793	-0.8932
1	1617.7	-13.969	**-12.168**	**-13.238**
2	114.66	-14.015	-10.774	-12.698
3	104.23	-14.041	-9.3593	-12.139
4	101.85	-14.133	-8.0098	-11.645
5	**95.175**	**-14.250**	-6.6863	-11.177

The bold font is used to signify the order of the VAR model which is favoured by the respective technique.

A study of the contents of Table 6.1.1 reveals a clear dichotomy concerning the order of the model which is preferred. It is apparent that the BIC and HQIC both favour only one lag on the endogenous variables. In contrast, though, from the sequential application of LR tests, at the five per cent level of significance, or examination of

[215] Recall that, in the case of earlier VAR systems, featuring first-differenced variables, the maximum order of model which was permitted was equal to 4. For consistency, with variables now contained in the form of levels, the longest length of lag which is allowed is equal to 5.

the values of the AIC, as many as five quarterly lags are believed to be optimal. On the basis of the discussion which was conducted in the Chapter Three, the decision is taken to adopt a cautious approach. Also, it would seem to be consistent for the VAR model to include five lags on the endogenous variables in the form of levels, when four lags were regarded as appropriate when the variables were expressed as first-differences.[216]

Having decided upon the order of the VAR model, it is now possible to perform the Johansen trace and maximum eigen-value tests for the purpose of inferring the cointegrating rank. A key consideration, though, is the framework that should be utilised when undertaking these tests. On the basis of the respective time plots, the series on at least log.(GDP) and log.(RW) would seem to incorporate a trend. Additionally, within the economics literature, the opinion has been expressed that, in equilibrium, the rate of price inflation is governed by, in part, the behaviour of GDP, relative to its trend path. Consequently, the most appropriate environment would appear to consist of Model 4, which, recall, accommodates a constant and trend term in the cointegration space, yet only a constant term in the data space. However, with the intention of applying the Dickey-Pantula procedure, the cointegration tests are also conducted in the context of the most reasonable rival model (i.e., Model 3), which allows for a constant term to be present in both the cointegration and data spaces of the VECM.

[216] It should be respected, though, that the comparable VAR model did not contain a time trend. Also, W*Δlog.(ROILP) does not accord exactly with the first-difference of W*log.(ROILP).

The two tables, below, show the results which are obtained from the sequential implementation of the trace and maximum eigen-value tests, using Model 3 as a framework.

Table 6.1.2: Results Obtained from the Sequential Application of Johansen's Trace Test in the Context of Model 3

Null Hypothesis: Value of r	Eigen-value	Value of λ_{TRACE}	5 per cent Critical Value	Probability Value
None	0.3862	226.00	159.53	0.0000
At most 1	0.3461	164.51	125.62	0.0000
At most 2	0.2685	110.98	95.754	0.0030
At most 3	0.2035	71.587	69.819	0.0359
At most 4	0.1390	42.917	47.856	0.1346
At most 5	0.1220	24.055	29.797	0.1981
At most 6	0.0589	7.6645	15.495	0.5019
At most 7	0.0001	0.0134	3.8415	0.9077

r signifies the number of cointegrating vectors.
Critical values of the trace statistic have been produced by MacKinnon *et al*. (1999).

Table 6.1.3: Results Obtained from the Sequential Application of Johansen's Maximum Eigen-Value Test in the Context of Model 3

Null Hypothesis: Value of r	Eigen-value	Value of λ_{MAX}	5 per cent Critical Value	Probability Value
None	0.3862	61.495	52.363	0.0045
At most 1	0.3461	53.530	46.231	0.0071
At most 2	0.2685	39.390	40.078	0.0596
At most 3	0.2035	28.671	33.877	0.1843
At most 4	0.1390	18.862	27.584	0.4252
At most 5	0.1220	16.390	21.132	0.2029
At most 6	0.0589	7.6512	14.265	0.4153
At most 7	0.0001	0.0134	3.8415	0.9077

r signifies the number of cointegrating vectors.
Critical values of the maximum eigen-value statistic have been produced by MacKinnon *et al*. (1999).

Upon viewing the contents of the Table 6.1.2 and 6.1.3, it is evident that if the chosen level of significance is five per cent then contrasting inferences are drawn from having performed sequentially the trace and maximum eigen-value tests. Having applied the succession of trace tests, the suggestion is that there are present as many as four cointegrating relationships. However, on the basis of the maximum eigen-value tests, the data would seem to deny the existence of more than two cointegrating equations.

There are now shown, below, the corresponding tables, having elected to undertake the cointegration analysis within the environment of Model 4.

Table 6.1.4: Results Obtained from the Sequential Application of Johansen's Trace Test in the Context of Model 4

Null Hypothesis: Value of r	Eigen-value	Value of λ_{TRACE}	5 per cent Critical Value	Probability Value
None	0.3862	269.64	187.47	0.0000
At most 1	0.3723	208.14	150.56	0.0000
At most 2	0.3444	149.47	117.71	0.0001
At most 3	0.2643	96.262	88.804	0.0130
At most 4	0.1574	57.593	63.876	0.1508
At most 5	0.1339	36.020	42.915	0.2056
At most 6	0.0927	17.907	25.872	0.3502
At most 7	0.0438	5.6466	12.518	0.5064

r signifies the number of cointegrating vectors.
Critical values of the trace statistic have been produced by MacKinnon *et al*. (1999).

Table 6.1.5: Results Obtained from the Sequential Application of Johansen's Maximum Eigen-Value Test in the Context of Model 4

Null Hypothesis: Value of r	Eigen-value	Value of λ_{MAX}	5 per cent Critical Value	Probability Value
None	0.3862	61.503	56.705	0.0155
At most 1	0.3723	58.670	50.600	0.0060
At most 2	0.3444	53.206	44.497	0.0045
At most 3	0.2643	38.669	38.331	0.0457
At most 4	0.1574	21.573	32.118	0.5268
At most 5	0.1339	18.113	25.823	0.3686
At most 6	0.0927	12.261	19.387	0.3913
At most 7	0.0438	5.6466	12.518	0.5064

r signifies the number of cointegrating vectors.
Critical values of the maximum eigen-value statistic have been produced by MacKinnon *et al*. (1999).

Upon inspecting the figures which are contained in Table 6.1.4 and Table 6.1.5, it is apparent that, on this occasion, the same outcome is achieved, irrespective of which of the two procedures is implemented. Whether trace or maximum eigen-value tests are performed, at the five per cent level of significance, the conclusion which is reached is that there are four cointegrating relationships involving the endogenous I(1) variables.

As was mentioned in Chapter Five, the Dickey-Pantula principle provides an objective approach towards deciding upon simultaneously the cointegrating rank and the form of VECM to adopt as a basis for analysis. Table 6.1.6, below, presents the earlier results in a manner which facilitates the application of this technique.

Table 6.1.6: Results Obtained from the Application of the Dickey-Pantula Procedure

Null Hypothesis: Value of r	Type of VECM			Type of VECM	
	Model 3	Model 4		Model 3	Model 4
	λ_{TRACE}	λ_{TRACE}		λ_{MAX}	λ_{MAX}
None	226.00	269.64		61.495	61.503
At most 1	164.51	208.14		53.530	58.670
At most 2	110.98	149.47		39.390*	53.206
At most 3	71.587	96.262		28.671	38.669
At most 4	42.917*	57.593		18.862	21.573

* denotes the first occasion on which it is not possible to reject Ho at the five per cent level of significance.

Regarding the above table, it is found that, upon strictly adhering to the Dickey-Pantula procedure, using either the trace test or the λ_{MAX} test and having chosen the five per cent level of significance, Model 3 seems the more appropriate environment within which to conduct the empirical investigation. Having performed trace tests, it is evident that there are considered to be four cointegrating equations. In contrast, though, reliance upon maximum eigen-value tests encourages the view to be held that there exist only two equilibrium relationships.

Thus far, the system tests of cointegration have been undertaken without attempting the finite-sample correction which was advocated by both Reimers (1992) and Cheung and Lai (1993). It will subsequently be demonstrated that a dramatic alteration to the conclusions arises from scaling the computed values of the test statistics in the manner which was recommended by Reimers. Initially, in the context of Model 3, both the trace and maximum eigen-value tests are, once again, sequentially performed. However, on this occasion, the original computed values of the λ_{TRACE} and λ_{MAX} have been transformed through employing $(T-n \cdot p)/T$ as a multiple.[217]

[217] Recall that, in this context, T denotes the sample size, n signifies the number of endogenous variables and p indicates the order of the VAR model.

Table 6.1.7: Results Obtained from the Application of Johansen's Trace Test in the Context of Model 3, with Allowance for a Finite-Sample Adjustment

Null Hypothesis: Value of r	Eigen-value	Value of $[(T–n\cdot p)/T]*\lambda_{TRACE}$	5 per cent Critical Value
None	0.3862	154.26	159.53
At most 1	0.3461	112.28	125.62
At most 2	0.2685	75.747	95.754
At most 3	0.2035	48.861	69.819
At most 4	0.1390	29.292	47.856
At most 5	0.1220	16.418	29.797
At most 6	0.0589	5.2314	15.495
At most 7	0.0001	0.0091	3.8415

r signifies the number of cointegrating vectors.
Critical values of the trace statistic have been produced by MacKinnon *et al*. (1999).

Table 6.1.8: Results Obtained from the Application of Johansen's Maximum Eigen-Value Test in the Context of Model 3, with Allowance for a Finite-Sample Adjustment

Null Hypothesis: Value of r	Eigen-value	Value of $[(T–n\cdot p)/T]*\lambda_{MAX}$	5 per cent Critical Value
None	0.3862	41.973	52.363
At most 1	0.3461	36.536	46.231
At most 2	0.2685	26.885	40.078
At most 3	0.2035	19.569	33.877
At most 4	0.1390	12.874	27.584
At most 5	0.1220	11.187	21.132
At most 6	0.0589	5.2222	14.265
At most 7	0.0001	0.0091	3.8415

r signifies the number of cointegrating vectors.
Critical values of the maximum eigen-value statistic have been produced by MacKinnon *et al*. (1999).

A study of the contents of Table 6.1.7 and 6.1.8 reveals that, given the selection of the five per cent level of significance, no matter whether a preference is exhibited for utilising a trace test or a maximum eigen-value test, the same outcome emerges. To be more specific, it is a feature of both tables that the very first computed value of the (transformed) test statistic does not exceed the corresponding critical value. Hence, in both cases, the inference is drawn of no cointegration. However, from closer scrutiny of Table 6.1.7, it is apparent that the null hypothesis, Ho: r = 0, is very close to being rejected, such that the notion of there being one cointegrating relationship should not be readily dismissed.

Correspondingly, the trace and maximum eigen-value tests are now conducted, adopting as a framework, Model 4, having suitably adjusted the computed values of λ_{TRACE} and λ_{MAX}. The associated results are shown in Table 6.1.9 and 6.1.10.

Table 6.1.9: Results Obtained from the Sequential Application of Johansen's Trace Test in the Context of Model 4, with Allowance for a Finite-Sample Adjustment

Null Hypothesis: Value of r	Eigen-value	Value of $[(T–n \cdot p)/T]*\lambda_{TRACE}$	5 per cent Critical Value
None	0.3862	184.04	187.47
At most 1	0.3723	142.06	150.56
At most 2	0.3444	102.02	117.71
At most 3	0.2643	65.702	88.804
At most 4	0.1574	39.309	63.876
At most 5	0.1339	24.585	42.915
At most 6	0.0927	12.222	25.872
At most 7	0.0438	3.8540	12.518

r signifies the number of cointegrating vectors.
Critical values of the trace statistic have been produced by MacKinnon *et al*. (1999).

Table 6.1.10: Results Obtained from the Sequential Application of Johansen's Maximum Eigen-Value Test in the Context of Model 4, with Allowance for a Finite-Sample Adjustment

Null Hypothesis: Value of r	Eigen-value	Value of $[(T-n \cdot p)/T]*\lambda_{MAX}$	5 per cent Critical Value
None	0.3862	41.978	56.705
At most 1	0.3723	40.044	50.600
At most 2	0.3444	36.315	44.497
At most 3	0.2643	26.393	38.331
At most 4	0.1574	14.724	32.118
At most 5	0.1339	12.363	25.823
At most 6	0.0927	8.3683	19.387
At most 7	0.0438	3.8540	12.518

r signifies the number of cointegrating vectors.
Critical values of the maximum eigen-value statistic have been produced by MacKinnon *et al*. (1999).

Upon viewing the contents of Table 6.1.9 and Table 6.1.10, it is apparent that, in each case, the first computed value of the test statistic is less than the corresponding critical value. However, once again, with respect to the trace test, the computed value is sufficiently adjacent to the critical value for the possibility of cointegration still to be entertained.

For the purpose of implementing the Dickey-Pantula procedure in conjunction with the scaled values of the test statistics, Table 6.1.11 is assembled.

Table 6.1.11: Results Obtained from the Implementation of the Dickey-Pantula Procedure, with Allowance for a Finite-Sample Adjustment to the Computed Values of the Test Statistics

Null Hypothesis: Value of r	Type of VECM			Type of VECM	
	Model 3	Model 4		Model 3	Model 4
	[(T-n·p)/T]* λ_{TRACE}	[(T-n·p)/T]* λ_{TRACE}		[(T–n·p)/T]* λ_{MAX}	[(T–n·p)/T]* λ_{MAX}
None	154.26*	184.04		41.973*	41.978
At most 1	112.28	142.06		36.536	40.044
At most 2	75.747	102.02		26.885	36.315
At most 3	48.861	65.702		19.569	26.393
At most 4	29.292	39.309		12.874	14.724

* denotes the first occasion on which it is not possible to reject Ho at the five per cent level of significance.

A strict interpretation of the results which are presented in Table 6.1.11 requires the conclusion that Model 3 is the more suitable framework for conducting both types of test and that there is no evidence of cointegration. However, upon adopting greater leniency and being prepared to reject a null hypothesis when the computed value of a statistic is in the vicinity of the five per cent critical value, a revised decision is merited on the basis of the trace test. Assuming a more relaxed approach, an initial two rejections of the null hypothesis that there is no cointegration would be followed by an acceptance of the null hypothesis, Ho: at most 1 cointegrating vector, operating in the context of Model 3.

Unfortunately, then, the cointegration analysis which has been performed so far has provided no clear guidance concerning the number of equilibrium relationships which exist between the endogenous variables. Perhaps, the suggestion of the results is that the inclusion of a linear trend term in the cointegrating space is unnecessary. However, the inferred number of long-run equations has ranged from zero to four, with the verdict having been seen to be sensitive to the type of test which is undertaken, the use of a finite-sample correction, and the level of significance which is adopted when conducting a hypothesis test.

As was mentioned in Chapter Five, as opposed to determining the order of the VAR model and the cointegrating rank in sequence, there is the scope to take the two decisions simultaneously by inspecting values of an information criterion. First, in the context of Model 3, consideration will be given to the values of the AIC and BIC for each of five different lag lengths ($p = 1, 2, 3, 4, 5$), combined with five different values of r ($= 0, 1, 2, 3, 4$). In all cases, the estimation period extends from 1973q4 to 2005q1.

Table 6.1.12: Values of the AIC and BIC, Corresponding to Different Combinations of Order of VAR Model (p) and Number of Cointegrating Vectors (r) in the Context of Model 3

Order of VAR Model (p)		Number of Cointegrating Vectors (r)				
		r = 0	r = 1	r = 2	r = 3	r = 4
p = 1	AIC	-13.693	-13.176	-13.320	-13.375	-13.356
p = 1	BIC	-12.072	**-12.636**	-12.420	-12.114	-11.735
p = 2	AIC	-13.845	-13.514	-13.611	-13.639	-13.564
p = 2	BIC	-10.784	-11.533	-11.270	-10.938	-10.502
p = 3	AIC	-13.908	-13.620	-13.702	-13.676	-13.631
p = 3	BIC	-9.4057	-10.199	-9.9200	-9.5339	-9.1288
p = 4	AIC	-13.978	-13.620	-13.705	-13.721	-13.679
p = 4	BIC	-8.0348	-8.7583	-8.4826	-8.1389	-7.7363
p = 5	AIC	**-14.030**	-13.487	-13.658	-13.716	-13.690
p = 5	BIC	-6.6470	-7.1838	-6.9945	-6.6930	-6.3064

In all cases, the estimation period is 1973q4–2005q1.
The minimum value that is achieved of the information criterion is shown in bold.

With reference to Table 6.1.12, it is apparent that the AIC and BIC are responsible for very different selections. The lowest value of the AIC is obtained by setting p = 5 and r = 0. Consequently, the AIC is exhibiting a preference for an unrestricted VAR model, with the lack of a long-run element, rather than any type of VECM. If the first column of figures is ignored then the minimum value of the AIC is associated with p = 4 and r = 3. In contrast, the BIC favours a model which incorporates a single equilibrium relationship but includes no lags on the endogenous variables, expressed as first-differences.

The same calculations are performed in the context of Model 4. The resultant values of the AIC and BIC are displayed in Table 6.1.13.

Table 6.1.13: Values of the AIC and BIC Corresponding to Different Combinations of Order of VAR Model (p) and Number of Cointegrating Vectors (r) in the Context of Model 4

Order of VAR Model (p)		Number of Cointegrating Vectors (r)				
		r = 0	r = 1	r = 2	r = 3	r = 4
p = 1	AIC	-13.969	-13.305	-13.467	-13.577	-13.564
p = 1	BIC	-12.168	**-12.743**	-12.522	-12.249	-11.853
p = 2	AIC	-14.015	-13.545	-13.652	-13.732	-13.683
p = 2	BIC	-10.774	-11.542	-11.266	-10.964	-10.532
p = 3	AIC	-14.041	-13.655	-13.721	-13.743	-13.689
p = 3	BIC	-9.3593	-10.210	-9.8941	-9.5336	-9.0965
p = 4	AIC	-14.133	-13.610	-13.755	-13.787	-13.773
p = 4	BIC	-8.0098	-8.7256	-8.4880	-8.1369	-7.7399
p = 5	AIC	**-14.250**	-13.471	-13.667	-13.819	-13.856
p = 5	BIC	-6.6863	-7.1455	-6.9586	-6.7284	-6.3828

In all cases, the estimation period is 1973q4 – 2005q1.
When r = 0, the unrestricted VAR model is allowed to include, as a regressor, a linear time trend.
The minimum value that is achieved of the information criterion is shown in bold.

A study of the above table indicates that the choices which are made by the AIC and BIC are unaffected by the presence of a deterministic trend term within the VAR model. Again, with respect to the AIC, the optimal combination consists of p = 5 and r = 0. Were the figures in the first column to be disregarded, though, the AIC now considers the most highly parameterised model to be appropriate, for which p = 5 and r = 4. In contrast, the BIC appears to reward simplicity. Once more, the type of VECM which is favoured by this criterion accommodates a single cointegrating relationship yet no lags on the endogenous variables, contained in the form of first-differences.

It may be concluded that this further analysis, which has involved a study of the values of two well-established information criteria in different settings, for twenty-five pairs of values of p and r, has failed to be especially productive. Consequently, a different approach is now adopted towards establishing the number of equilibrium relationships. Using Model 3 as a framework, setting p = 5, the maximum eight cointegrating equations will be inspected with the objective of assessing whether or not there can be lent to any of these an acceptable economic interpretation. For each cointegrating vector, β_i, which is regarded as being consistent with economic theory, time plots of $\beta_i'x_t$ and $\beta_i'R_{1t}$ are constructed to permit an approximate check on whether or not the linear combination of I(1) variables succeeds in delivering a stationary time series.[218]

[218] Recall that R_{1t} is formed by purging x_{t-1} of its short-run dynamics.

Table 6.1.14: Cointegrating Vectors Arising from the Application of the Johansen Procedure in the Context of Model 3

Endogenous Variable	β_1	β_2	β_3	β_4
log.(GDP)	-14.362	-10.620	-44.797	-11.559
log.(ROILP)	2.8504	2.7630	-1.0661	1.5081
W*log.(ROILP)	-4.0780	-0.4507	0.2766	0.7226
PINF	2.0280	0.0371	-0.0514	1.5851
TB	-0.4397	0.4352	-0.3402	0.5258
LTIR	0.2115	-1.9277	-0.6626	-1.1312
log.(RW)	17.240	-8.2263	36.462	14.166
log.(REER)	1.6113	-14.154	10.400	-1.6143

Endogenous Variable	β_5	β_6	β_7	β_8
log.(GDP)	20.302	-7.8020	11.109	2.5118
log.(ROILP)	-2.4677	1.8171	0.9821	-2.0935
W*log.(ROILP)	-0.9281	-0.8488	-0.0770	-1.5132
PINF	0.5831	-0.2573	-0.6153	-0.0890
TB	0.0500	0.2125	-0.0143	0.1458
LTIR	0.1076	0.0616	0.0944	0.2816
log.(RW)	-25.794	17.383	-21.136	-9.2240
log.(REER)	10.483	-3.9964	7.9815	3.5525

Estimation period: 1973q4-2005q1.
The underlying VAR model includes five lags on the endogenous variables.

An inspection of the figures in the first column of Table 6.1.14 suggests that the first cointegrating equation has the interpretation of an equilibrium relationship for the real exchange rate. In support of this statement, a positive association can be seen between log.(REER) and each of log.(GDP) and TB. Also, there appears to be a negative correlation between the exchange rate variable and the rate of consumer price inflation. Furthermore, the estimated parameters indicate a tendency for a rise (fall) in the price of oil to stimulate a depreciation (an appreciation) in the U.K.'s currency. However, the negative correspondence between the movements in these two variables is observed to become weaker, the larger is the ratio of the U.K.'s exports to its consumption of crude oil.[219]

The estimates of the parameters which are located in the second column of Table 6.1.14 can be regarded as being in accordance with an equation for the long-term rate of interest. This assertion is founded upon the negative relationship that is observed between LTIR and each of log.(GDP) and log.(REER). Also, it is based upon the positive association that prevails between LTIR and the percentage rate of consumer price inflation. Furthermore, the data indicate a positive connection between developments in the rate of interest and the real price of oil, the strength of which is reduced (enhanced) by an increase (a decrease) in the ratio of the U.K.'s exports to its consumption of crude oil.

In contrast to the cointegrating vectors which are located in the first two columns, those which enter further to the right cannot be easily interpreted in terms of economic theory. Hence, encouragement is received to proceed on the basis that there exist two long-run equilibrium relationships. However, prior to the incorporation of the long-run restrictions within the VECM, line graphs are produced of $\beta_1'x_t$ and $\beta_2'x_t$ (and, correspondingly, $\beta_1'R_{1t}$ and $\beta_2'R_{1t}$), in attempt to gain confirmation that the series which have been created are stationary.

[219] Indeed, should the U.K.'s exports exceed its consumption of crude oil then the equation indicates that, *ceteris paribus*, the real effective exchange rate will move in the same direction as the price of oil.

Figure 6.1.1: Line Graph of First Disequilibrium Variable

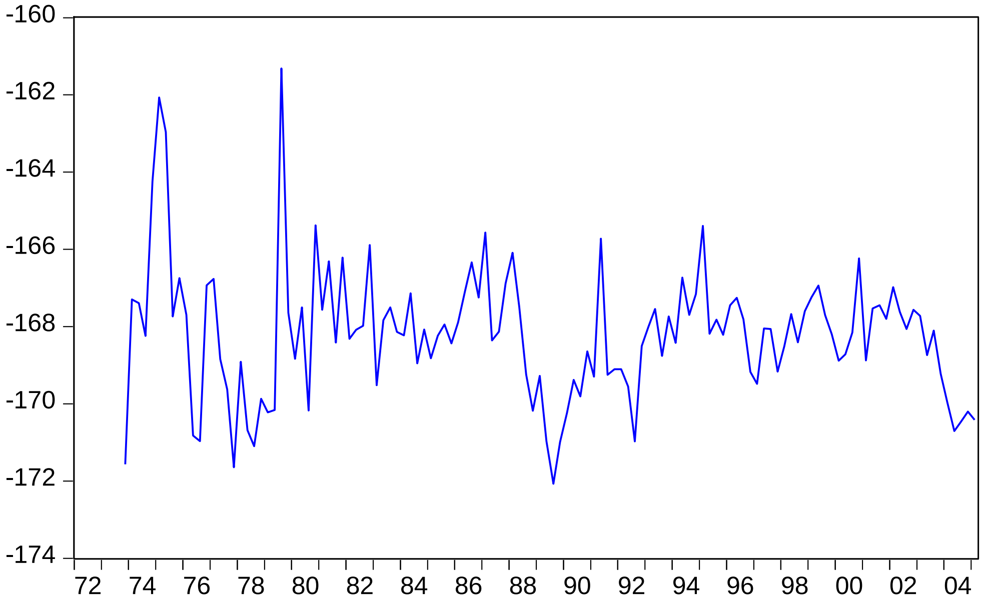


Figure 6.1.2: Line Graph of Second Disequilibrium Variable

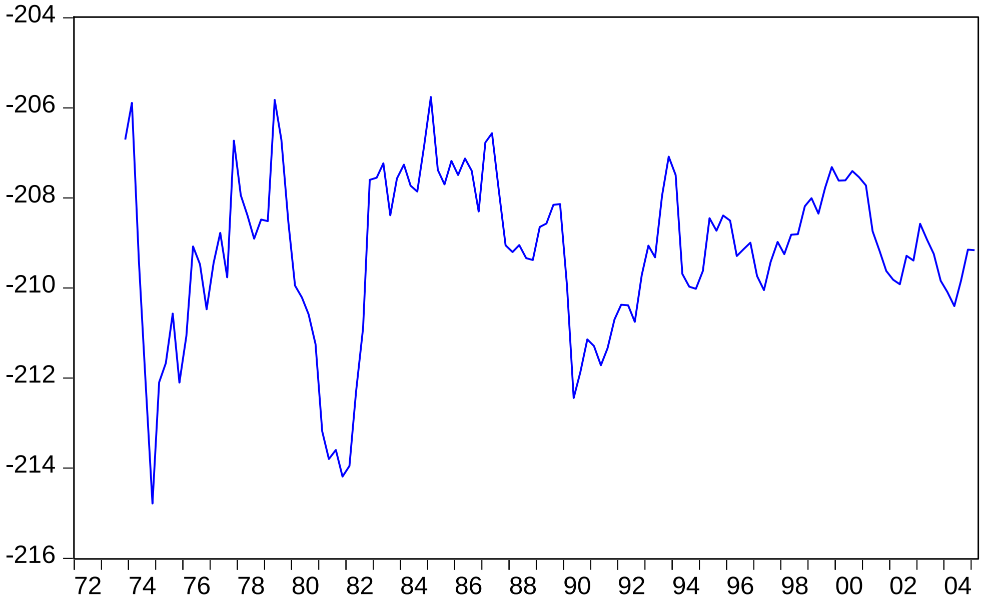


Figure 6.1.3: Line Graph of the Variable Formed from the First Cointegrating Vector and the Endogenous Variables, Purged of their Short-Run Dynamics

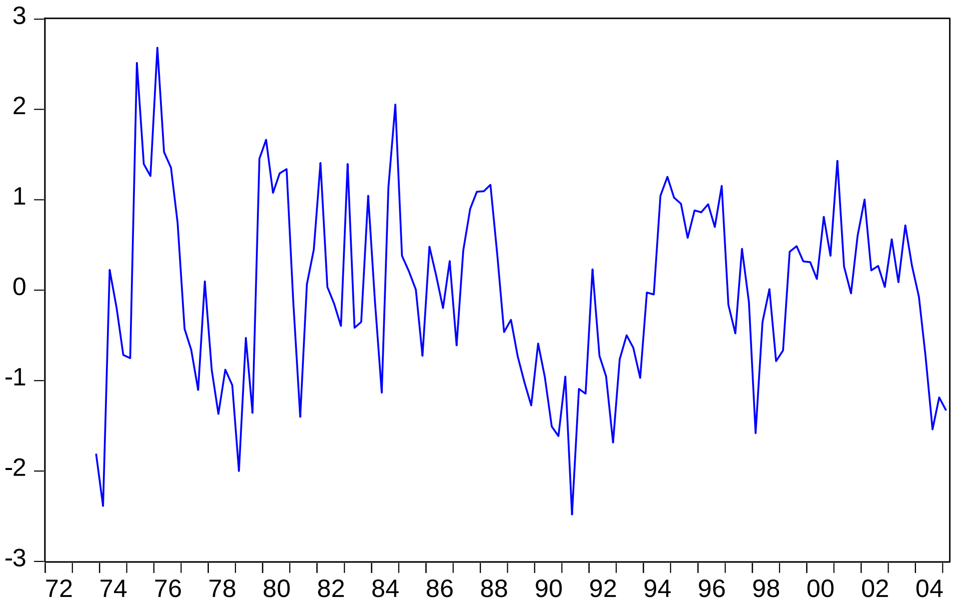
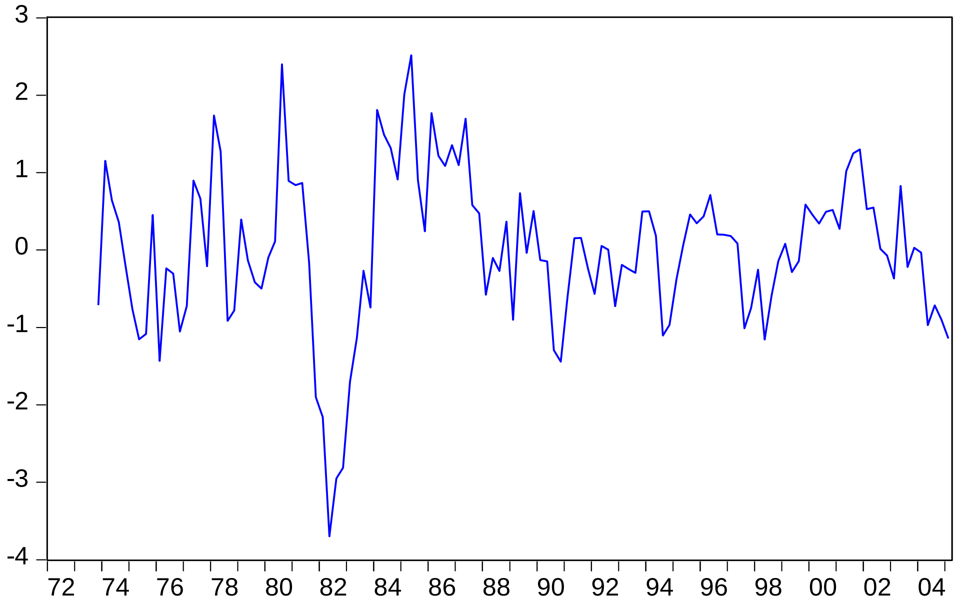


Figure 6.1.4: Line Graph of the Variable Formed from the Second Cointegrating Vector and the Endogenous Variables, Purged of their Short-Run Dynamics



Figures 6.1.1, 6.1.2, 6.1.3 and 6.1.4 show the line graphs of $\beta_1'x_t$, $\beta_2'x_t$, $\beta_1'R_{1t}$ and $\beta_2'R_{1t}$, respectively. All four of these time plots appear to conform to a stationary time series. Hence, there would seem to be a statistical justification for progressing to

the estimation of a reduced-form VECM, which incorporates two long-run, equilibrium relationships between the I(1) variables. The cointegrating equations are normalised in terms of log.(REER) and LTIR. For the purpose of achieving exact identification, different variables are excluded from the two equations. More specifically, while LTIR does not feature in the equation for log.(REER), log.(RW) is omitted from the equation for the long-term rate of interest. Table 6.1.15, below, details the estimates of the elements of the two cointegrating vectors, beneath which, in brackets, are provided the associated values of the t statistics.

Table 6.1.15: Estimates of the Parameters of the Cointegrating Equations

Endogenous Variable	Estimates of Parameters within:	
	Cointegrating Vector 1 (β_1)	Cointegrating Vector 2 (β_2)
log.(GDP)	-267.37 (-2.8609)	9.5654 (6.5078)
log.(ROILP)	54.300 (5.3827)	-2.2571 (-5.4429)
W*log.(ROILP)	-71.070 (-6.8050)	1.3120 (3.3576)
PINF	34.990 (5.8727)	-0.5500 (-2.5127)
TB	-6.7490 (-4.3428)	-0.1234 (-2.2145)
LTIR	0.0000	1.0000
log.(RW)	281.30 (2.4970)	0.0000
log.(REER)	1.0000	7.3273 (4.9324)

An equation is presented so that all of the endogenous variables feature on its left-hand side.

A study of the estimates in Table 6.1.15 reveals that the signs do not conflict with theoretical expectations. However, in the first column, the magnitudes are a cause for concern and encourage the suggestion that it would have been more appropriate to have interpreted the corresponding equation as a description of the long-run behaviour of the real wage. It should be respected, though, that the subsequent short-run analysis is unaffected by the variable which is chosen for normalisation.

6.2 Construction and Estimation of Vector Error-Correction Models

The equations of the VECM are estimated by OLS, using data from 1973q4 to 2005q1. To enable comparisons to be undertaken with earlier VAR models, the system includes $W^*\Delta\log.(ROILP)_{t-i}$, rather than $\Delta(W^*\log.(ROILP))_{t-i}$ ($i = 0, 1, 2, 3, 4$). For each of the eight equations which comprise the VECM, the following table reports the value of the R-squared statistic, the value of the standard error of the regression (s.e.), the estimates of the two adjustment coefficients, together with the corresponding probability values.[220]

[220] The probability value relates to a two-tailed t test of the null hypothesis that the respective coefficient is equal to zero.

Table 6.2.1: Results Obtained from Application of OLS Estimation to the VECM

Dependent Variable	R-Squared	s.e.	Estimates of Adjustment Coefficients (probability values)	
			α_{i1}	α_{i2}
Δlog.(GDP)$_t$	0.4248	0.0077	0.00009 (0.0432)	-0.0002 (0.8760)
Δlog.(ROILP)$_t$	0.3915	0.1533	-0.0012 (0.1770)	0.0065 (0.8058)
W*Δlog.(ROILP)$_t$	0.2931	0.1133	0.0002 (0.6992)	0.0234 (0.2326)
ΔPINF$_t$	0.6569	0.6215	-0.0100 (0.0053)	0.0579 (0.5890)
ΔTB$_t$	0.3314	1.1288	-0.00007 (0.9910)	-0.1266 (0.5157)
ΔLTIR$_t$	0.4895	0.5434	-0.0067 (0.0316)	-0.3029 (0.0017)
Δlog.(RW)$_t$	0.4726	0.0101	0.00006 (0.2925)	-0.0028 (0.1162)
Δlog.(REER)$_t$	0.3293	0.0335	-0.0002 (0.3688)	-0.0064 (0.2676)

Estimation period: 1973q4-2005q1

From a consideration of the figures in the final two columns of Table 6.2.1, it is apparent that each of the disequilibrium terms has a significant role to play in at least one of the eight short-run equations. Additionally, it is evident that, for both the exchange rate and the long-term rate of interest, any departure from equilibrium is followed by, in the next quarter, a movement towards the respective long-run path. However, on the basis of a closer inspection of the coefficient estimates, it seems that the adjustment of the interest rate is far more rapid than that of the exchange rate. It can be observed that, out of the sixteen probability values, only four of these are less than 0.05. Also, for five of the eight variables (including Δlog.$(REER)_t$), neither of the estimates of the two adjustment coefficients is significant at the five per cent level.[221]

In conjunction with the VECM, Granger-causality tests are subsequently performed. For convenience, the system of eight equations is presented in the following manner:

$$\Delta x_{it} = constant + \sum_{j=1}^{2} \alpha_{ij} z_{jt-1} + \sum_{j=1}^{8} \sum_{k=1}^{4} \psi_{ijk} \Delta x_{jt-k} + e_{it}, \quad (i = 1, 2, \ldots\ldots, 8). \tag{6.2.1}$$

With reference to equation (6.2.1), z_j (j = 1, 2) is denoting the jth disequilibrium term. Also, the assumption is made that the endogenous variables are ordered in such a way that Δx_7 and Δx_8 correspond to Δlog.(ROILP) and W*Δlog.(ROILP), respectively. For the purpose of testing whether or not the real price of oil Granger-causes endogenous variable i (i = 1, 2, ……, 6), the null hypothesis,

Ho: $\alpha_{i1} = 0$, $\alpha_{i2} = 0$, $\psi_{i7k} = 0$, (k = 1, 2, ……, 4),

is contrasted with the alternative hypothesis,

221 It should be recognised, though, that, with respect to the equation for Δlog.$(RW)_t$, an F test of the joint null hypothesis that both of the adjustment coefficients are equal to zero yields a significant result. In particular, $F(2, 91) = 4.0057$ (probability value = 0.0215).

Ha: at least one of $\alpha_{i1} \neq 0$, $\alpha_{i2} \neq 0$, $\psi_{i7k} \neq 0$, (k = 1, 2, ……, 4).

The results of the six F tests which are conducted are presented in Table 6.2.2, below.

Table 6.2.2: Results of Granger-Causality Tests Performed in Conjunction with Equation (6.2.1)

	Endogenous Variable		
	Δlog.(GDP)	Δlog.(REER)	Δlog.(RW)
F(6, 91) (probability value)	2.3539 (0.0369)	1.2856 (0.2718)	3.2290 (0.0064)
	Endogenous Variable		
	ΔPINF	ΔTB	ΔLTIR
F(6, 91) (probability value)	8.0006 (0.0000)	1.8153 (0.1048)	6.8580 (0.0000)

Estimation period: 1973q4-2005q1.

It is apparent from inspecting the contents of Table 6.2.2 that four out of the six probability values are less than 0.05. Consequently, at the five per cent level of significance, the inference can be drawn that the real price of oil Granger-causes Δlog.(GDP), Δlog.(RW), ΔPINF and ΔLTIR. In relation to the short-term rate of interest, the computed value of the F statistic is close to exceeding the critical value corresponding to the ten per cent level of significance. Only for the exchange rate does there seem to be a clear lack of evidence of a causal relationship. If a comparison is made with the results which have been reported in Table 4.8.3.1 then it is possible to conclude that the addition of the disequilibrium terms to the short-run model has served to strengthen, in particular, the relationship between U.K. G.D.P. and the real price of oil.[222]

Consideration is also given to whether or not the real price of oil is Granger-caused by any of the six macroeconomic variables. This entails, for each of $j = 1, 2, \ldots\ldots, 6$, performing an F test of the null hypothesis,

Ho: $\alpha_{71} = 0, \alpha_{72} = 0, \psi_{7jk} = 0, (k = 1, 2, \ldots\ldots, 4)$,

against the alternative hypothesis,

Ha: at least one of $\alpha_{71} \neq 0, \alpha_{72} \neq 0, \psi_{7jk} \neq 0, (k = 1, 2, \ldots\ldots, 4)$.

The resultant computed values of the F statistics and the associated probability values are displayed in Table 6.2.3, below.

[222] It should be appreciated, though, that the extended linear VAR model and the VECM have been estimated over slightly different sample periods.

Table 6.2.3: Results of Granger-Causality Tests with Δlog.(ROILP)$_t$ as the Dependent Variable

	Right-Hand-Side Variable		
	Δlog.(GDP)	Δlog.(REER)	Δlog.(RW)
F(6, 91) (probability value)	2.9579 (0.0110)	1.8085 (0.1061)	0.6019 (0.7281)
	Right-Hand-Side Variable		
	ΔPINF	ΔTB	ΔLTIR
F(6, 91) (probability value)	1.4203 (0.2154)	1.1114 (0.3620)	0.6997 (0.6505)

Estimation period: 1973q4-2005q1.

Upon examining the figures which are shown in Table 6.2.3, it can be seen that only one of the six probability values is below 0.05. Thus, only for Δlog.(GDP) is it is possible to reject Ho in favour of Ha at the five per cent level of significance.[223] For Δlog.(REER), the computed value of the F statistic comes near to exceeding the critical value corresponding to the ten per cent level of significance. However, on the basis of the results that have been obtained, there is scant evidence to suggest that the real price of oil is Granger-caused by any of Δlog.(RW), ΔPINF, ΔTB and ΔLTIR.

It may be recalled that, in section 4.9 of this thesis, within- and post-sample evidence was obtained of asymmetric effects on the growth of output of increases and decreases in the real price of oil. On this basis, it may be considered to be appropriate to examine the econometric consequences of adding as explanatory variables to the respective equation in the extended asymmetric VAR model the two disequilibrium

[223] As has been mentioned earlier in this thesis, this would seem to be a plausible result if the business cycles that are associated with the major industrialised countries have been synchronised.

terms. Following application of OLS estimation over the interval, 1974q2-2005q1, the value of the R-squared statistic is 0.5002, while the standard error of the regression is calculated to be 0.0072. Both of these figures represent an improvement upon the corresponding values which are contained in Table 6.2.1, although it is recognised that the sample periods are not identical.

Offering greater detail, with regard to the equation for Δlog.(GDP)$_t$ which was included in the extended asymmetric VAR model, OLS estimation resulted in values of the coefficient of determination and the standard error of the regression that were equal to 0.4684 and 0.0074, respectively.[224] Hence, there would seem to be a statistical justification for the introduction of the disequilibrium variables. Indeed, when an F test is performed of the joint null hypothesis that both of the adjustment coefficients are equal to zero, a probability value of 0.0821 is achieved. However, individually, the two terms lack significance, being associated with probability values of 0.1441 and 0.5493.

In the context of the extended asymmetric equation for Δlog.(GDP)$_t$, which also accommodates the disequilibrium variables, it is possible to conduct Granger-causality tests. With respect to a null hypothesis which states that both of the adjustment parameters, as well as the coefficients which are attached to the four quarterly lags on SOPI (SOPD), are equal to zero, the computed value of the F(6, 81) statistic is 2.5411 (1.1715), which corresponds to a probability value of 0.0264 (0.3298). Hence, in spite of the modification to the extended asymmetric equation,

[224] See Table 4.9.5.1 in Chapter Four.

the key inference appears to be preserved that increases in the real price of oil are of greater relevance than decreases for the subsequent behaviour of output growth.

The statistical information that has been gathered in connection with the VECM is suggestive of the two disequilibrium components not enhancing the explanation of the variation in Δlog.(ROILP), W*Δlog.(ROILP), ΔTB or Δlog.(REER). Additional analysis is now performed for the purpose of deciding upon the variables which can be treated as weakly exogenous. As a starting point, a summary is provided of values of different measures of goodness of fit, corresponding to the equations which comprise the extended linear VAR model and those which are represented by specification (6.2.1).

Table 6.2.4: Values of Measures of Goodness of Fit Relating to the Extended Linear VAR Model and the VECM (Equation (6.2.1))

Extended Linear VAR Model				
Dependent Variable	R-squared	S.E.	AIC	BIC
Δlog.(GDP)$_t$	0.3155	0.0084	-6.5035	-5.7645
Δlog.(ROILP)$_t$	0.3624	0.1545	-0.6786	0.0605
W*Δlog.(ROILP)$_t$	0.2757	0.1128	-1.3069	-0.5679
ΔPINF$_t$	0.5999	0.6612	2.2292	2.9683
ΔTB$_t$	0.3602	1.1405	3.3196	4.0587
ΔLTIR$_t$	0.4243	0.5751	1.9502	2.6893
Δlog.(RW)$_t$	0.4233	0.0104	-6.0726	-5.3335
Δlog.(REER)$_t$	0.3391	0.0334	-3.7403	-3.0012

Estimation period: 1973q3-2005q1

(continued)

VECM				
Dependent Variable	R-squared	S.E.	AIC	BIC
Δlog.(GDP)$_t$	0.4248	0.0077	-6.6549	-5.8670
Δlog.(ROILP)$_t$	0.3915	0.1533	-0.6824	0.1054
W*Δlog.(ROILP)$_t$	0.2931	0.1133	-1.2874	-0.4995
ΔPINF$_t$	0.6569	0.6215	2.1169	2.9047
ΔTB$_t$	0.3314	1.1288	3.3104	4.0982
ΔLTIR$_t$	0.4895	0.5434	1.8481	2.6360
Δlog.(RW)$_t$	0.4726	0.0101	-6.1226	-5.3347
Δlog.(REER)$_t$	0.3293	0.0335	-3.7233	-2.9354

Estimation period: 1973q4-2005q1

It should be appreciated that the equations comprising the two models which are being compared have not been estimated over identical sample periods. Hence, there is no guarantee that the value of the R-squared statistic will not fall upon expanding the set of explanatory variables. Indeed, Table 6.2.4 reveals that, in two cases, a reduction occurs in the value of the coefficient of determination in progressing from the VAR model to the VECM. In contrast, for six of the endogenous variables, a rise in value can be witnessed, with the most marked improvements corresponding to the equations for Δlog.(GDP)$_t$ and ΔLTIR$_t$. The computation of the value of the standard error of the regression takes into consideration the number of estimated parameters, thus, can be viewed as a more discerning measure of goodness of fit. An inspection of the figures in the second columns of the two parts of the table indicates that, in all but two instances, the value of this statistic decreases in moving from the top to the bottom section. Proportionally, the diminution is greatest for Δlog.(GDP)$_t$, while the two equations for which the value of the standard error becomes larger are those which describe the behaviour of W*Δlog.(ROILP)$_t$ and Δlog.(REER)$_t$.

Regarding the two columns of the table which include the values of the AIC, it can be seen that, for six out of the eight variables, the VECM is associated with a lower value of the statistic than the extended linear VAR model. In contrast, from inspecting the two columns which contain the values of the BIC, it is found that, for only four of the variables is the performance of the VECM superior to that of its rival. For four of the endogenous variables (Δlog.(GDP), ΔPINF, ΔLTIR and Δlog.(RW)), the information criteria are in agreement that the VECM provides an improved framework for analysis. Only for Δlog.(REER) and W*Δlog.(ROILP) would both the AIC and BIC maintain that no benefit has arisen from the introduction of long-run restrictions into the VAR model.

An observation that has been made earlier in this thesis is that the process of comparing the empirical performances of different models over the full sample period is possibly handicapped by the occurrence of extraordinary events which occurred in 1979. Consequently, the VECM is also estimated over the shorter period, 1982q1-2005q1, following which the resultant values of the R-squared statistic and the standard error of the regression are contrasted with those which correspond to the extended linear VAR model.

Table 6.2.5: Values of Measures of Goodness of Fit Relating to the VECM and the Extended Linear VAR Model (Reduced Sample Period)

		VECM			Extended Linear VAR Model	
Dependent Variable		R-squared	S.E.		R-squared	S.E.
Δlog.(GDP)$_t$		0.5534	0.0045		0.4972	0.0047
Δlog.(ROILP)$_t$		0.4571	0.1291		0.4197	0.1312
W*Δlog.(ROILP)$_t$		0.4242	0.1259		0.3943	0.1269
ΔPINF$_t$		0.6812	0.4398		0.6520	0.4518
ΔTB$_t$		0.4292	0.8257		0.3599	0.8596
ΔLTIR$_t$		0.5457	0.4090		0.3999	0.4622
Δlog.(RW)$_t$		0.4624	0.0062		0.4475	0.0062
Δlog.(REER)$_t$		0.4675	0.0307		0.4615	0.0304

Estimation period: 1982q1-2005q1.

An inspection of the corresponding values of the coefficient of determination that are reported in Table 6.2.5 reveals that, for each of Δlog.(GDP), ΔPINF and Δlog.(RW), the introduction of the disequilibrium terms serves to increase the value of the R-squared statistic by 0.06, 0.03 and 0.01, respectively. In contrast, for the full sample period, the increments which were achieved consisted of 0.11, 0.06 and 0.05. However, as can be seen in Figure 4.1.1.2, Figure 4.1.4.2 and Figure 4.1.5.2, in Chapter Four, a feature of all three of the time series on these variables is that, in their early stages, there occurs a sharp movement which appears to be subsequently corrected.[225] Consequently, over the full data period, a disequilibrium term is offered the potential for fulfilling an explanatory role which is not available from 1982q1. Thus, it is important to be aware of the possibility of the estimated effects of the

[225] The clearest examples consist of 1979q2/1979q3 for Δlog.(GDP), 1979q3/1979q4 for ΔPINF, and 1974q1/1974q2 for Δlog.(RW), which are connected to the occurrence of industrial action, the imposition of an indirect tax, and the enforcement of an incomes policy, respectively.

disequilibrium terms being spurious in the context of the error-correction equations for Δlog.(GDP), ΔPINF and Δlog.(RW). This issue will now be explored by undertaking a post-sample analysis.[226]

6.3 Post-Sample Analysis

To begin this section, the estimated equations of the VECM are employed to produce forecasts of the values of seven of the endogenous variables over the interval, 2005q2–2008q1. For each variable, the values of five summary measures of predictive performance are provided in Table 6.3.1, below.[227]

[226] The same broad finding emerges from consideration of the equation for Δlog.(GDP) within the extended asymmetric model. In particular, when estimation is performed over the full sample period, the addition of the two disequilibrium variables succeeds in raising the value of the coefficient of determination by 0.03. In contrast, when estimation is conducted over the restricted period, the augmentation serves to increase the value of the R-squared statistic by 0.02.

[227] W*Δlog.(ROILP) is excluded from this analysis, on account of being a hybrid measure.

Table 6.3.1: Summary of the Post-Sample Performance of the Estimated Equations Comprising the VECM

Endogenous Variable	Mean Square Error	Mean Error (s.e)	Mean Absolute Error	Root Mean Square Error	Median Square Error
Δlog.(GDP)	0.3055×10^{-4}	0.0044 (0.0010)	0.0050	0.0055	0.1951×10^{-4}
Δlog.(ROILP)	0.0120	-0.0076 (0.0329)	0.0939	0.1094	0.0065
ΔPINF	0.2885	-0.4209 (0.1006)	0.4579	0.5371	0.2388
ΔTB	0.2082	0.1124 (0.1333)	0.3660	0.4562	0.0905
ΔLTIR	0.0704	-0.0646 (0.0776)	0.2370	0.2653	0.0713
Δlog.(RW)	0.6283×10^{-4}	0.0030 (0.0022)	0.0068	0.0079	0.4112×10^{-4}
Δlog.(REER)	0.6181×10^{-3}	-0.0123 (0.0065)	0.0209	0.0249	0.3025×10^{-3}

Prediction period: 2005q2-2008q1.
Forecasts are based upon equations which have been estimated over a fixed period, 1973q4-2005q1.
s.e. denotes standard error of the sample mean, which is calculated by applying the square root operator to the ratio of the sample variance of a prediction error to the number of forecasts.

Consideration of the figures in the second column creates cause for concern with respect to the specifications for $\Delta \log.(GDP)_t$ and $\Delta PINF_t$. In the case of the former, the ratio of the arithmetic mean forecast error to the associated standard error is equal to 4.25. Moreover, upon examination of the individual forecast errors, eleven out of twelve are found to be positive. There is also strong evidence to suggest that the predictions of the change in consumer price inflation are biased. For this variable, the ratio of the average forecast error to the standard error is equal to -4.18. Additionally, following scrutiny of the individual forecast errors, ten out of twelve are seen to be negative.

On account of earlier empirical results relating to Δlog.(GDP), in an attempt to solve the problem of systematic underprediction, the decision is taken to conduct a post-sample analysis in conjunction with an asymmetric function. In particular, a specification is achieved by permitting the respective equation which is contained in the extended asymmetric VAR model to incorporate additionally the two disequilibrium variables. The resultant equation is estimated over the interval, 1974q2-2005q1, following which forecasts are generated of the dependent variable from 2005q2 to 2008q1. On this occasion, the arithmetic average forecast error is calculated to be 0.0046, which is associated with a standard error of 0.00075. On the basis of these values, bias still prevails. Indeed, every one of the values of Δlog.(GDP)$_t$, (t = 2005q2, 2005q3, ……, 2008q1), is underpredicted by the estimated equation.

It is evident that the biased predictions have occurred as a consequence of the incorporation of the two disequilibrium terms in the equation for Δlog.(GDP)$_t$. It would seem logical, then, to investigate whether or not this feature can be eliminated by the removal of one of these variables. On the basis that z_{1t-1} is associated with a greater degree of significance than z_{2t-1}, the decision is taken to extract the former.

Initially, the error-correction equation for Δlog.(GDP)$_t$, with no allowance for asymmetry, is estimated over the interval, 1973q4–2005q1. The following values of the within-sample statistics are obtained: R-squared = 0.3982; standard error of the regression = 0.0079; AIC = -6.6256; SIC = -5.8602.[228] With reference to the post-sample analysis, extending from 2005q2 to 2008q1, the average prediction error is calculated as 0.0019, with an accompanying standard error of 0.0011.[229] Additionally, the estimated model is responsible for nine underpredictions and three overpredictions of the quarterly growth of output.

Secondly, the extended asymmetric equation for Δlog.(GDP)$_t$, which additionally includes z_{2t-1}, is estimated using data on the dependent variable from 1974q2 to 2005q1. On this occasion, the following values of the measures of goodness of fit are achieved: R-squared = 0.4868; standard error of the regression = 0.0073; AIC = -6.7423; SIC = -5.7871.[230] In conjunction with the forecasts of Δlog.(GDP)$_t$ (t = 2005q2, 2005q3, ……, 2008q1), the average prediction error is calculated to be 0.0025. On the basis that the corresponding standard error is 0.0008,[231] it would seem reasonable to infer that the forecasts are biased. Indeed, consideration of the individual errors reveals that the estimated equation yields eleven (out of a possible twelve) underpredictions.

In relation to modelling Δlog.(GDP), the information that has been gleaned from the post-sample analysis which has been undertaken suggests that there is no empirical advantage to be gained from combining disequilibrium and asymmetric terms in a specification. Thus, it seems that it is necessary to take a decision concerning which of the two features to incorporate. From a theoretical perspective, it is desirable for a

[228] Additionally, the single disequilibrium term is associated with a probability value of 0.1263.
[229] The ratio of the average forecast error to the standard error is equal to 1.8404.
[230] Furthermore, the disequilibrium term is associated with a probability value of 0.0902.
[231] The value of the ratio of the average forecast error to the standard error is equal to 3.1442.

short-run equation to accommodate one or more long-run equilibrium relationships. Consequently, the choice will be made of the error-correction equation for Δlog.(GDP)$_t$, with no allowance for asymmetry, yet including z_{2t-1} (but not z_{1t-1}) as an explanatory variable, on condition that its forecasting performance is seen not to be significantly inferior to that of the corresponding equation which is embedded within the extended asymmetric VAR model.

As a first step, the values of the root mean square prediction error are contrasted for the two competing equations. Whereas the estimated error-correction equation gives rise to a root mean square error which is equal to 0.0038, the estimated asymmetric equation is associated with a much lower value of 0.0026, which corresponds to a 31.5 per cent reduction. However, for a more formal assessment of the equality of forecast accuracy, there is performed the two-tailed test which has been proposed by Harvey *et al*. (1997). It may be recalled that, in connection with this test, the null hypothesis assumes the form of Ho: $E[d_t] = 0$, where $d_t = e_{it}^2 - e_{jt}^2$. In the current context, e_i and e_j denote the prediction errors relating to the error-correction and asymmetric equations, respectively.

The application of the test that has been proposed by Harvey *et al*. involves the computation of the value of the statistic, S_1^*, which should be compared with a critical value which has been extracted from the table of the t distribution, corresponding to a number of degrees of freedom which equates with the number of forecasts less one. The calculated value of 2.7562 is considerably in excess of the respective five per cent critical value of 2.201, thereby enabling the inference to be drawn that the error-correction and asymmetric equations do not possess equal forecast accuracy. On the basis of the strength of this result, it is considered suitable to regard as the optimal specification an equation for Δlog.(GDP) which caters for asymmetric effects of unanticipated increases and decreases in the real price of oil, yet permits no reaction to any form of long-run disequilibrium.[232]

With respect to the macroeconomic variable, ΔPINF, in contrast to Δlog.(GDP), the results that were obtained from earlier empirical investigation (in Chapter Four) showed that forecast accuracy was adversely affected by allowing for asymmetry. Consequently, for the price inflation variable, it seemed unadvisable to assemble an equation which permitted disequilibrium terms to reside alongside SOPI, SOPD, W*SOPI and W*SOPD. Thus, in an attempt to eliminate bias, a more suitable strategy is considered to be to operate in the context of the extended linear equation for ΔPINF and, rather than accommodating both of the disequilibrium terms within this framework, to include merely the variable which appeared to have the weaker influence, i.e., z_{2t-1}.[233]

Following estimation of the constructed equation for $\Delta PINF_t$ over the interval, 1973q4–2005q1, the following values of the within-sample statistics are obtained: R-squared = 0.6261; standard error of the regression = 0.6452; AIC = 2.1868; SIC = 2.9522.[234] With respect to the post-sample performance of this equation, an average forecast error of -0.1420 is produced, which can be compared with a standard error of 0.1053. The ratio of the former to the latter is -1.3494, which suggests that the problem of bias has been largely eradicated. It can also be observed that, out of the twelve forecast errors, seven are negative and five are positive.

232 Essentially, then, in the forthcoming analysis, GDP will be treated as a weakly exogenous variable.
233 See Table 6.2.1.
234 The disequilibrium term is associated with a probability value of 0.0149.

Estimation of the equations of the VECM and the subsequent empirical analysis which was conducted enables a specification to be tentatively recommended for each of the endogenous variables. Currently, equation (6.2.1) would appear to be an acceptable description of the short-run behaviour of ΔLTIR and Δlog.(RW). In contrast, for ΔPINF, a benefit has been seen to be derived from disregarding one of the disequilibrium terms. Also, for Δlog.(GDP), the preferred function refrains from incorporating long-run restrictions, yet allows for asymmetric effects of increases and decreases in the real price of oil. For the remaining variables, the incorporation of either z_{1t-1} or z_{2t-1} in the respective function can be regarded as superfluous.

For the three macroeconomic variables which are perceived to respond to situations of long-run disequilibria, familiar tests are now undertaken to compare the predictive performance of the respective error-correction equation with that of the corresponding equation within the extended linear VAR model. Initially, the test for equal forecast accuracy that was proposed by Harvey *et al*. (1997) is applied. Hence, for each of six variables, the value of the statistic, S_1^*, is computed and presented in Table 6.3.2, below.

Table 6.3.2: Computed Values of the S_1^* Statistic for the purpose of Testing for the Equality of the Forecast Accuracy of Error-Correction Equations and Equations within the Extended Linear VAR Model

	Endogenous Variable		
	ΔPINF	ΔLTIR	Δlog.(RW)
Value of S_1^*	-0.6882	1.6001	-0.3856

With reference to the above table, the test procedure has been implemented in such a way that a positive value of S_1^* implies that the error-correction equation achieves a greater degree of accuracy, while a negative value indicates the superiority of the equation within the extended linear VAR model. In absolute terms, the largest of the three value of S_1^* can be seen to be 1.6001, relating to the forecasts of $\Delta LTIR_t$ (t = 2005q2, 2005q3, ……, 2008q1). However, on the basis that the critical value corresponding to the ten per cent level of significance is 1.796, for none of the seven variables is it possible to infer that that the competing equations do not have the same predictive capability.

With regard to the same three variables, there is also a desire to perform forecast encompassing tests. In particular, the tests which have been proposed by Harvey *et al*. (1998) and Clark and McCracken (2001) will both be applied to each of the endogenous variables which feature in the above table.[235] With reference to the former test, there is a requirement to compute the value of the S_1^* statistic. However, in contrast to when comparing the forecast accuracy of competing equations, d_t is defined as $e_{it}(e_{it} – e_{jt})$, where e_i and e_j denote the forecast errors corresponding to the equation within the VAR model and the error-correction equation, respectively. Also, recall that, in the context of forecast encompassing, a one-tailed test is undertaken of the null hypothesis, Ho: $E[d_t] = 0$, against the alternative hypothesis, Ha: $E[d_t] > 0$.

[235] On this occasion, the encompassing test that has been recommended by Clark and McCracken is suitable for use, on the basis that the equation which enters the extended linear VAR model is nested within the respective error-correction equation.

Table 6.3.3: Computed Values of the S_1^* Statistic for the purpose of Testing for Forecast Encompassing in Relation to the Error-Correction Equations and the Equations of the Extended Linear VAR Model

	Endogenous Variable		
	ΔPINF	ΔLTIR	Δlog.(RW)
Value of S_1^*	0.2268	1.9995	0.5411

Table 6.3.3, above, shows the computed values of S_1^* for the three endogenous variables. The five and ten per cent critical values which have been extracted from the table of the t distribution, corresponding to 11 degrees of freedom, consist of 1.796 and 1.363, respectively. Consequently, for ΔLTIR, it is possible, at a conventional level of significance, to reject Ho in favour of Ha. Thus, for the long-term rate of interest the inference can be drawn that the forecasts which are produced by the equation from the extended linear VAR model do not encompass those which are achieved, having estimated the error-correction equation.

The broad design of the test which was advocated by Clark and McCracken (2001) is the same as the encompassing test which has just been performed. However, the former requires the computation of the statistic, ENC-NEW, the value of which should be compared with a critical value that has been obtained from Appendix Table 5 (p. 37) within an earlier paper that was produced by these authors (Clark and McCracken (2000)). For each of the three endogenous variables, the calculated value of ENC-NEW is shown in Table 6.3.4, below.

Table 6.3.4: Computed Values of the ENC-NEW Statistic for the purpose of Testing for Forecast Encompassing in Relation to the Error-Correction Equations and the Equations of the Extended Linear VAR Model

	Endogenous Variable		
	ΔPINF	ΔLTIR	Δlog.(RW)
Value of ENC-NEW	0.2522	5.0917	0.9042

The critical values are partly governed by π, which represents the ratio of the number of forecasts to the number of observations that are employed in estimation. Also, they are a function of the number of additional regressors (k_2) in moving from the restricted to the unrestricted equation. Thus, for all three of the variables, π is approximately equal to 0.1. However, whereas, for ΔPINF, k_2 is equal to 1, for the remaining two variables, the parameter assumes a value of 2. Consequently, for ΔPINF, alone, the 90th and 95th percentiles are in the region of 0.322 and 0.489, respectively. In contrast, for ΔLTIR and Δlog.(RW), the corresponding percentiles are in the vicinity of 0.500 and 0.729.

From a comparison of the computed values of ENC-NEW with the relevant critical values, it is evident that, for both of ΔLTIR and Δlog.(RW), at the five per cent level of significance, it is possible to reject the null hypothesis which asserts that the equation from the extended linear VAR model encompasses the error-correction equation. In contrast, for ΔPINF, the data are seen not to contradict the null hypothesis. On the whole, though, the results of the tests for forecast encompassing reinforce the earlier conclusions.

6.4 Construction of a Conditional VECM

The empirical results which have been reported in sections 6.2 and 6.3 of this chapter give encouragement to treating Δlog.(GDP), Δlog.(ROILP), W*Δlog.(ROILP), ΔTB and Δlog.(REER) as weakly exogenous. Strictly, the conditional VECM should be comprised of equations for only ΔPINF, ΔLTIR and Δlog.(RW).[236] However, on account of one of the cointegrating equations receiving the interpretation of a long-run equation for the real exchange rate, there is a desire to allow the latter to respond systematically to situations of disequilibrium. Hence, in spite of the absence of supporting statistical evidence, $\Delta\text{log.(REER)}_t$ is initially permitted to feature as a dependent variable in the conditional system.[237]

For the purpose of clarification, the conditional VECM is formed from the error-correction equations for ΔPINF_t, ΔLTIR_t, $\Delta\text{log.(RW)}_t$ and $\Delta\text{log.(REER)}_t$, which are augmented by the inclusion of, as explanatory variables, $\Delta\text{log.(GDP)}_t$, $\Delta\text{log.(ROILP)}_t$, $W^*\Delta\text{log.(ROILP)}_t$ and ΔTB_t. In its company is a marginal model, which is comprised of specifications for the latter four variables, which, importantly, do not accommodate disequilibrium terms. The conditional equations are estimated by OLS,[238] following which consideration is given to the significance of the estimated effects of the right-hand-side variables. If it is apparent that the equations incorporate common regressors which are associated with minimal explanatory

[236] Recall that the equation for ΔPINF_t includes only a single disequilibrium variable.

[237] The possibility is being entertained of the significance of the respective disequilibrium term being enhanced in the act of refining the model.

[238] The application of OLS estimation is usually justified by each equation including the same set of regressors. However, it needs to be recognised that, within the conditional model which is constructed, the equation for ΔPINF_t does not feature z_{1t-1}.

power then these will be removed, thereby producing the ‘parsimonious’ conditional VECM.

Table 6.4.1: Results Obtained from the Application of OLS Estimation to the Conditional VECM

Dependent Variable	R-squared	Standard Error	BG(4)	ARCH(1)
$\Delta PINF_t$	0.6550	0.6338	0.5229 (0.7192)	0.0116 (0.9141)
$\Delta LTIR_t$	0.6522	0.4587	0.9989 (0.4130)	0.0001 (0.9941)
$\Delta log.(RW)_t$	0.5677	0.0094	1.4611 (0.2215)	0.4800 (0.4884)
$\Delta log.(REER)_t$	0.4058	0.0323	1.6259 (0.1754)	0.1088 (0.7415)

Estimation period: 1973q4-2005q1.
BG(4) denotes the value of the Breusch-Godfrey F statistic, which is computed for the purpose of testing for up to fourth-order autocorrelation in the disturbance terms.
ARCH(1) signifies the value of the ARCH chi-square statistic, which is computed for the purpose of testing whether or not the disturbance terms are homoskedastic.
Probability values are contained in parentheses.

Upon observing the figures which are contained in the final two columns of Table 6.4.1, it seems that the four error-correction equations are free from diagnostic problems. More specifically, none of the values of the Breusch-Godfrey statistic are of a sufficient magnitude to be able to reject, at a conventional level of significance, the null hypothesis that the error terms are non-autocorrelated. Also, the results of the four chi-square tests which are conducted permit the inference to be drawn that the conditional variances of the error terms do not accord with an ARCH(1) process.[239]

[239] *EViews* permits the application of system-wide chi-square tests for autocorrelated disturbance terms, although maintains that the tests are valid only for lags which are longer than the order of the model. Also, the package issues the warning that probability values may not be accurate in the presence of lagged dependent variables. Nevertheless, relating to tests for up to eighth-order

In connection with the four equations comprising the conditional VECM, observation of the coefficient estimates, values of the respective t statistics and associated probability values encourages the omission from the model of $\Delta PINF_{t-4}$, ΔTB_{t-2}, ΔTB_{t-3}, ΔTB_{t-4}, $\Delta log.(REER)_{t-3}$ and $\Delta log.(REER)_{t-4}$. Following the application of an exclusion test, a computed value of the chi-square statistic is achieved which is equal to 17.775. For twenty-four degrees of freedom, the corresponding probability value is 0.8138, which permits these six variables to be discarded and the parsimonious conditional VECM to be constructed.

Table 6.4.2: Results Obtained from the Application of OLS Estimation to the Parsimonious Conditional VECM

Dependent Variable	R-squared	Standard Error	BG(4)	ARCH(1)
$\Delta PINF_t$	0.6369	0.6291	0.5795 (0.6782)	0.0174 (0.8950)
$\Delta LTIR_t$	0.6391	0.4520	0.5765 (0.6804)	0.0099 (0.9205)
$\Delta log.(RW)_t$	0.5417	0.0093	1.7118 (0.1544)	2.3685 (0.1264)
$\Delta log.(REER)_t$	0.3741	0.0320	0.9911 (0.4167)	0.0550 (0.8146)

Estimation period: 1973q4-2005q1.
BG(4) denotes the value of the Breusch-Godfrey F statistic, which is computed for the purpose of testing for up to fourth-order autocorrelation in the disturbance terms.
ARCH(1) signifies the value of the ARCH chi-square statistic, which is computed for the purpose of testing whether or not the disturbance terms are homoskedastic.
Probability values are contained in parentheses.

With regard to Table 6.4.2, as is to be expected, by virtue of having omitted six explanatory variables, there occurs a fall in each of the values of the coefficient of

autocorrelation, the probability values are sufficiently high to seek to draw the inference that there is an absence of serial correlation.

determination. However, for the reason that, statistically, the contribution of these variables was found to be negligible, in each case, a decrease is experienced in the value of the standard error of the regression. On the basis of the information which is presented in the final two columns of the above table, the parsimonious equations are void of diagnostic problems. In particular, the figures which are contained in the third column indicate a lack of evidence to refute the notion that the error terms are non-autocorrelated. Additionally, in the fourth column, none of the probability values appears to be less than 0.10. Hence, at a conventional level of significance, the null hypothesis that the disturbance terms are homoskedastic cannot be rejected in favour of the alternative hypothesis which asserts the suitability of an ARCH(1) model.[240]

6.5 Construction and Estimation of the Structural VECM

In accordance with the proposed methodology, given that statistical support has been obtained for a parsimonious form of the conditional VECM, construction now takes place of the structural VECM. The latter is created by extending the former by admitting contemporaneous relationships between the four endogenous variables, ΔPINF, ΔLTIR, Δlog.(RW) and Δlog.(REER). On account of the simultaneous nature of the relationships, it is necessary to estimate the structural model using a system method. Also, it is essential to address the issue of the identification of each of the four constituent equations.

[240] Again, while respecting their limitations, the system-wide tests that are performed for up to eighth-order autocorrelation in the disturbance terms are suggestive of a lack of serial correlation.

Table 6.5.1: Variables Omitted from the Equations Comprising the Structural VECM

Dependent Variable			
$\Delta PINF_t$	$\Delta LTIR_t$	$\Delta log.(RW)_t$	$\Delta log.(REER)_t$
z_{1t-1}, $\Delta log.(GDP)_{t-i}$, (i = 2, 3), $W^*\Delta log.(ROILP)_{t-2}$, $\Delta PINF_{t-4}$, ΔTB_{t-i}, (i = 0, 1, 2, 3, 4), $\Delta LTIR_{t-i}$, (i = 2, 3, 4), $\Delta log.(RW)_{t-i}$, (i = 2, 3), $\Delta log.(REER)_{t-i}$, (i = 1, 2, 3, 4).	$\Delta log.(GDP)_{t-i}$, (i = 1, 3), $\Delta log.(ROILP)_{t-i}$, (i = 3, 4), $W^*\Delta log.(ROILP)_{t-i}$, (i = 0, 1, 3, 4), $\Delta PINF_{t-i}$, (i = 0, 1, 2, 3, 4), ΔTB_{t-i}, (i = 1, 2, 3, 4), $\Delta LTIR_{t-i}$, (i = 2, 3, 4), $\Delta log.(RW)_{t-4}$, $\Delta log.(REER)_{t-i}$, (i = 0, 1, 2, 3, 4).	z_{1t-1}, $\Delta log.(GDP)_{t-i}$, (i = 1, 2, 4), $\Delta log.(ROILP)_{t-i}$, (i = 2, 4), $W^*\Delta log.(ROILP)_{t-i}$, (i = 2, 4), $\Delta PINF_{t-i}$, (i = 1, 2, 3, 4), ΔTB_{t-i}, (i = 0, 1, 2, 3, 4), $\Delta LTIR_{t-i}$, (i = 1, 2, 3, 4), $\Delta log.(RW)_{t-3}$, $\Delta log.(REER)_{t-i}$, (i = 0, 1, 2, 3, 4).	z_{1t-1}, $\Delta log.(GDP)_{t-i}$, (i = 0, 1, 2, 3, 4), $\Delta log.(ROILP)_{t-i}$, (i = 0, 1, 2, 3, 4), $W^*\Delta log.(ROILP)_{t-i}$, (i = 0, 1, 2, 3, 4), $\Delta PINF_{t-i}$, (i = 1, 3, 4), ΔTB_{t-i}, (i = 2, 3, 4), $\Delta LTIR_{t-i}$, (i = 0, 1, 2, 3, 4), $\Delta log.(RW)_{t-i}$, (i = 0, 1, 2, 3, 4), $\Delta log.(REER)_{t-i}$, (i = 3, 4).

The application of 3SLS estimation[241] necessitates excluding different combinations of variables from the four structural equations. Table 6.5.1, above, shows, based upon a consideration of goodness-of-fit, the variables which are omitted from each equation.

[241] Using *EViews*, 3SLS estimation allows for both heteroskedastic and contemporaneously correlated error terms. Implementation of the procedure involves initially Two-Stage Least Squares estimation being conducted in conjunction with an unweighted system. On the basis of the associated residuals, an estimate is formed of the variance-covariance matrix of the stochastic error terms, which is employed for the purpose of undertaking transformations which have the objective of eliminating cross-equation correlations. Two-stage Least Squares estimation is subsequently performed in conjunction with the transformed model. The instruments consist of all of the variables which enter the right-hand sides of the equations which form the conditional (pre-parsimonious) VECM.

With reference to the sequential testing procedure that is adopted in order to arrive at the parsimonious form of the structural model, a policy is adopted of always retaining in an individual equation both a constant term and at least one of the disequilibrium variables, regardless of whether or not a statistical justification exists for so doing. The inclusion or exclusion of the remaining variables is governed by the outcome of chi-square tests which are performed at the ten per cent level of significance. The results which are achieved following application of Three-Stage Least Squares estimation to the parsimonious structural VECM are shown in Table 6.5.2, below. In particular, in each cell, there is reported the sum of the estimates of the coefficients which are attached to the specified variable on the right-hand side of the respective equation. Additionally, in brackets, there is presented the probability value corresponding to a chi-square test of the null hypothesis that asserts that each of the coefficients is equal to zero.

Table 6.5.2: Results Obtained from Application of 3SLS Estimation to the Parsimonious Structural VECM

Right-Hand-Side Variable		Dependent Variable			
		$\Delta PINF_t$	$\Delta LTIR_t$	$\Delta log.(RW)_t$	$\Delta log.(REER)_t$
z_1		-	-0.0070 (0.0000)	-	-
z_2		0.1626 (0.0105)	-0.2318 (0.0000)	-0.0004 (0.6102)	-0.0024 (0.3826)
Δlog.(GDP)		60.892 (0.0000)	-51.195 (0.0000)	0.1497 (0.0014)	-
Δlog.(ROILP)		5.4187 (0.0000)	1.3774 (0.0000)	0.0157 (0.0000)	-
W*Δlog.(ROILP)		-5.4505 (0.0000)	-0.9044 (0.0553)	-0.0191 (0.0005)	-
ΔPINF		-0.8855 (0.0000)	-	-0.0057 (0.0000)	0.0209 (0.0000)
ΔTB		-	0.2510 (0.0000)	-	-0.0022 (0.0000)
ΔLTIR		0.5026 (0.0000)	0.1360 (0.0158)	0.0035 (0.0263)	-
Δlog.(RW)		-21.617 (0.0000)	35.068 (0.0000)	0.3561 (0.0000)	-
Δlog.(REER)		6.4457 (0.0063)	-	-	0.1736 (0.0000)

Estimation period: 1973q4-2005q1.
Each cell contains the sum of the estimates of the coefficients which are attached to the respective right-hand-side variable.
The number in parentheses indicates the probability value corresponding to a chi-square test of the null hypothesis that each of the coefficients is equal to zero.

An initial observation that can be made, on the basis of the contents of Table 6.5.2, is that, having refined the original structural VECM in order to achieve the more concise representation, not all of the estimates of the adjustment coefficients are significant. Indeed, an implication of the results which are reported in the table is that both the real wage and the real effective exchange rate are weakly exogenous variables.[242] It is apparent that, when different forms of disequilibrium arise, movements in the long-term rate of interest and the rate of consumer price inflation alone assume responsibility for maintaining stable long-run relationships.

With reference to the equation for $\Delta PINF_t$, from studying the initial figure in the third row, which is attached to Δlog.(GDP), it would seem that short-term increases in the growth of output are inflationary.[243] Additionally, it is of interest to discover that the sums of the estimated coefficients which are attached to Δlog.(ROILP) and W*Δlog.(ROILP) are similar in size but different in terms of sign. The implication of this finding is that, in a situation in which the U.K.'s exports of crude oil are minimal, compared to its consumption of this commodity, a rise in the price of oil would exert significant upward pressure on consumer price inflation. In contrast, though, during a period of at least approximate equality between exports and consumption of crude oil, an oil price hike would be of limited consequence for price developments in the U.K..

With respect to the equation for $\Delta LTIR_t$, the estimates of the coefficients suggest that a change in Δlog.(ROILP) tends to stimulate a significant movement in the dependent variable in the same direction. However, it is evident that an increase in the U.K.'s exports of crude oil, in relation to its consumption, serves to weaken, if

[242] In spite of the desire for z_{1t-1} to enter the equation for Δlog.(REER)$_t$, the data did not support its retention. Indeed, z_{2t-1} was found to exert the stronger influence on the dependent variable.

[243] In offering comments on the empirical results, a deliberate attempt is made to refrain from contrasting estimates with any theoretical expectations, respecting that, within this thesis, the decision has been taken for the findings to be predominantly determined by the data.

not eliminate, the connection between the long-term rate of interest and the real price of oil.

From consideration of the figures in the third column of the table, the growth of real wages seems to benefit from a faster rate of change of economic activity. Also, although quantitatively not strong, there is observed a significant positive association between Δlog.(RW) and Δlog.(ROILP), which is diminished by a rise in the ratio of the U.K.'s exports to its consumption of crude oil. In contrast, from an examination of the entries in the final column, under no circumstance is the real effective exchange rate sensitive to short-run developments in the real price of oil. Indeed, the behaviour of Δlog.(REER) is influenced by relatively few variables within the system, with merely changes in ΔPINF and ΔTB being seen to be of any relevance.

As was mentioned in an earlier footnote, *EViews* provides the potential to perform tests for autocorrelated disturbance terms in conjunction with a system of equations. More specifically, it permits the application of a multivariate version of a Box-Pierce/Ljung-Box chi-square test. Upon request, the package reports values of both a Q statistic and a related measure which has been subject to a small-sample correction. Although, strictly, these tests are not valid in the presence of lagged dependent variables, the results which are obtained may be indicative of any dynamic misspecification.

The recommendation is to test for an order of autocorrelation which exceeds the maximum length of lag on the variables which enter the model. Thus, in testing for up to eighth-order autocorrelation, the computed values of the chi-square statistics are associated with probability values of 0.6751 and 0.5597. The latter would seem to be sufficiently far above conventional significance levels such that no doubt is cast over the acceptability of the lag structure.

6.6 Estimation of the Marginal Model

The empirical analysis which is performed within this chapter proceeds by focusing upon the marginal model, which, recall, is comprised of equations for the variables within the VAR system which were inferred as being weakly exogenous. Consideration is given, first of all, to the equations for Δlog.(ROILP)$_t$, W*Δlog.(ROILP)$_t$ and ΔTB_t that include four lags on all of the eight variables, which entered the extended linear VAR model.

These three equations are estimated by OLS over an interval which extends from 1973q4 to 2005q1. In conjunction with each, a sequential testing procedure is implemented in an attempt to achieve a parsimonious representation of the data. In order to be able to accept a more concise specification, two broad conditions need to be satisfied. First, following the application of a Wald test of coefficient restrictions, the computed value of the respective F statistic should be less than the corresponding ten per cent critical value. Also, having conducted tests for autocorrelation and heteroskedasticity in the disturbance terms, no diagnostic problems should be revealed.

Table 6.6.1, below, indicates the variables which are excluded from the three equations, having adopted the general-to-specific modelling strategy. Table 6.6.2

subsequently shows the consequences of having applied OLS estimation to the resultant parsimonious specifications.[244]

Table 6.6.1: Variables Omitted from the Equations for Δlog.(ROILP)$_t$, W*Δlog.(ROILP)$_t$ and ΔTB$_t$

Dependent Variable		
Δlog.(ROILP)$_t$	W*Δlog.(ROILP)$_t$	ΔTB$_t$
Δlog.(GDP)$_{t-i}$, (i = 1, 2, 3), Δlog.(ROILP)$_{t-i}$, (i = 2, 3, 4), W*Δlog.(ROILP)$_{t-4}$, ΔPINF$_{t-i}$, (i = 1, 2, 3, 4), ΔTB$_{t-i}$, (i = 1, 3, 4), ΔLTIR$_{t-i}$, (i = 1, 2, 3, 4), Δlog.(RW)$_{t-i}$, (i = 1, 2, 3, 4), Δlog.(REER)$_{t-i}$, (i = 1, 2, 3, 4).	Δlog.(GDP)$_{t-i}$, (i = 1, 3, 4), Δlog.(ROILP)$_{t-i}$, (i = 1, 2, 3, 4), ΔPINF$_{t-i}$, (i = 1, 2, 3, 4), ΔTB$_{t-i}$, (i = 1, 2, 3, 4), ΔLTIR$_{t-i}$, (i = 1, 2, 3, 4), Δlog.(RW)$_{t-i}$, (i = 2, 3, 4), Δlog.(REER)$_{t-i}$, (i = 1, 2, 4).	Δlog.(GDP)$_{t-4}$, Δlog.(ROILP)$_{t-i}$, (i = 1, 2, 3), W*Δlog.(ROILP)$_{t-i}$, (i = 1, 2, 3), ΔPINF$_{t-i}$, (i = 1, 2, 3, 4), ΔTB$_{t-i}$, (i = 1, 2, 4), ΔLTIR$_{t-i}$, (i = 1, 2, 3, 4), Δlog.(RW)$_{t-i}$, (i = 2, 3, 4), Δlog.(REER)$_{t-i}$, (i = 1, 2, 3, 4).

[244] For completeness, the results are presented which are obtained from estimating the equation for W*Δlog.(ROILP)$_t$, although the manner of its construction compels little interest in the determination of values of this variable.

Table 6.6.2: Results Obtained following OLS Estimation of the Parsimonious Equations for Δlog.(ROILP)$_t$, W*Δlog.(ROILP)$_t$ and ΔTB_t

Right-Hand-Side Variable		Dependent Variable		
		Δlog.(ROILP)$_t$	W*Δlog.(ROILP)$_t$	ΔTB_t
Δlog.(GDP)		4.9766 (0.0007)	1.2044 (0.2687)	30.117 (0.0022)
Δlog.(ROILP)		-0.2548 (0.0429)	-	-2.9967 (0.0013)
W*Δlog.(ROILP)		0.4280 (0.0025)	0.1082 (0.0010)	3.0955 (0.0188)
ΔPINF		-	-	-
ΔTB		0.0309 (0.0079)	-	-0.1432 (0.0799)
ΔLTIR		-	-	-
Δlog.(RW)		-	1.4709 (0.0761)	22.790 (0.0141)
Δlog.(REER)		-0.9475 (0.0172)	-0.6950 (0.0134)	-
R-squared		0.2502	0.2104	0.1912
Standard Error of Regression		0.1495	0.1052	1.0903
BG(4)		0.3535 (0.8411)	1.6970 (0.1555)	1.2687 (0.2865)
ARCH(1)		0.0541 (0.8160)	0.9856 (0.3208)	0.1042 (0.7468)

Estimation period: 1973q4-2005q1.
Each cell corresponding to a right-hand-side variable contains the sum of the estimates of the respective coefficients. The number in parentheses indicates the probability value that is associated with an F test of the null hypothesis that each of the coefficients is equal to zero.
BG(4) signifies the computed value of the Breusch-Godrey F statistic for the purpose of testing for up to fourth-order autocorrelation in the disturbance term.
ARCH(1) indicates the computed value of the chi-square statistic for the purpose of testing for whether or not an ARCH(1) model describes the conditional variance of the disturbance term.
In relation to the diagnostic tests, probability values are shown in brackets.

When consideration is given to the contents of Table 6.6.2, an immediate observation that can be made relates to the equation for W*Δlog.(ROILP)$_t$. It is apparent that Δlog.(GDP)$_{t-2}$ has been retained in the equation, in spite of being associated with a lack of significance. However, the justification for the inclusion of this variable is that, in the event of its exclusion, autocorrelation is introduced into the respective disturbance terms.

From a study of the final column, it seems that movements in the real price of oil have implications for the future behaviour of the short-term rate of interest. However, as the ratio of exports to the consumption of crude oil rises, the influence of a change in Δlog.(ROILP) on ΔTB declines. The entries in the first column of Table 6.6.2 are suggestive of the U.K.'s macroeconomic performance affecting the real price of oil. In terms of probability values, the most significant contribution is provided by Δlog.(GDP).

Attention finally turns to the specification for Δlog.(GDP). It may be recalled that Δlog.(GDP) constitutes the macroeconomic variable for which the most conclusive evidence has been accumulated of asymmetric effects of an increase and a decrease in the real price of oil. Additionally, it was discovered not to be helpful to include in a short-run equation for output growth either of the two disequilibrium variables which emerged from the cointegration analysis. Consequently, if a function is being sought to characterise the behaviour of Δlog.(GDP) then it is recommended that reliance be placed upon the relationship which entered the extended asymmetric VAR model.

The original equation for Δlog.(GDP)$_t$ was estimated over the interval, 1974q2-2005q1, and incorporated on its right-hand side four quarterly lags on each of the macroeconomic indicators, as well as SOPI, SOPD, W*SOPI and W*SOPD. In this section, as was the case for the equations for Δlog.(ROILP)$_t$, W*Δlog.(ROILP)$_t$ and ΔTB$_t$, a sequential testing procedure is now implemented in an attempt to achieve an acceptable parsimonious representation of the data on Δlog.(GDP)$_t$.

The application of a general-to-specific modelling methodology allows the following variables to be discarded from the right-hand side of the equation for Δlog.(GDP)$_t$: Δlog.(GDP)$_{t-4}$; SOPI$_{t-i}$ (i = 1, 2); SOPD$_{t-i}$ (i = 1, 2, 3, 4); W*SOPI$_{t-i}$ (i = 1, 2, 4); W*SOPD$_{t-i}$ (i = 1, 2, 3, 4); ΔPINF$_{t-i}$ (i = 1, 2, 3, 4); ΔTB$_{t-i}$ (i = 1, 2, 3, 4); ΔLTIR$_{t-4}$; Δlog.(RW)$_{t-i}$ (i = 1, 2, 3, 4); and Δlog.(REER)$_{t-i}$ (i = 1, 2, 3). Table 6.6.3, below, shows the results which are achieved after having applied OLS estimation to the final, parsimonious equation.

Table 6.6.3: Results Obtained following OLS Estimation of the Parsimonious Equation for Δlog.(GDP)$_t$

Right-Hand-Side Variable	Δlog.(GDP)	SOPI	SOPD	W*SOPI	W*SOPD
Sum of Estimated Coefficients (Probability Value)	0.1053 (0.0150)	-0.0084 (0.0005)	-	0.0063 (0.0059)	-

(continued)

Right-Hand-Side Variable	ΔPINF	ΔTB	ΔLTIR	Δlog.(RW)	Δlog.(REER)
Sum of Estimated Coefficients (Probability Value)	-	-	-0.0014 (0.0004)	-	-0.0437 (0.0182)

Estimation period: 1974q2-2005q1.
Each cell corresponding to a right-hand-side variable contains the sum of the estimates of the respective coefficients. The number in parentheses indicates the probability value that is associated with an F test of the null hypothesis that each of the coefficients is equal to zero.

In connection with the estimated equation which features in Table 6.6.3, the values of the R-squared statistic and the standard error of the regression are 0.3481 and 0.0070, respectively. The value of the Breusch-Godfrey F statistic, which is computed for the purpose of testing for the presence of up to fourth-order autocorrelation in the disturbance term, is 0.1145, with an associated probability value of 0.9772. The value of the ARCH(1) chi-square statistic, which is generated in order to assess whether or not the disturbance terms are homoskedastic, is 13.833, for which the corresponding probability value is 0.0002.

An unwelcome feature, then, of the estimated equation for $\Delta\text{log.(GDP)}_t$ is the significant value of the ARCH(1) statistic. This diagnostic problem can be attributed to the erratic behaviour of output growth which arose from the Winter of Discontent. When the observations on the dependent variable, $\Delta\text{log.(GDP)}_t$ (t = 1979q1, 1979q2, 1979q3), are excluded from the sample period, the heteroskedasticity in the disturbance terms is eliminated.[245] Following the implementation of the general-to-specific methodology, a different set of variables emerges from before.[246] However,

[245] Corresponding to the final (specific) equation, the computed value of the ARCH(1) chi-square statistic is 0.0721, which is associated with a probability value of 0.7882.

[246] The variables which ultimately remain on the right-hand side of the equation consist of: $\Delta\text{log.(GDP)}_{t-3}$; SOPI_{t-i} (i = 1, 3, 4); W*SOPI_{t-i} (i = 1, 3); ΔPINF_{t-i} (i = 1, 4); ΔLTIR_{t-i} (i = 1, 2, 3, 4); $\Delta\text{log.(REER)}_{t-4}$.

in common with the previous selection, the four lags on SOPD and W*SOPD have no presence in the final equation.

From a study of the figures which are presented in Table 6.6.3, there is apparent a significant short-run relationship between the real price of oil and the growth of output. As was the case with the general equation for Δlog.(GDP)$_t$, which represented the starting point for the most recent analysis, there is evidence of asymmetric effects of an increase and a decrease in the real price of oil on the dependent variable. Indeed, the indication of the parsimonious specification is that a fall in the real price of oil is of no consequence whatsoever for output growth. The sums of the estimates of the coefficients which are attached to SOPI and W*SOPI suggest that, *ceteris paribus*, an unanticipated rise in the real price of oil serves to suppress the growth of G.D.P.. However, the influence of an upward movement in the real price of oil diminishes as the ratio of the U.K.'s exports to its consumption of crude oil becomes larger.[247]

6.7 Estimation of Revised Models[248]

Having estimated the parsimonious version of the structural VECM, on account of some key assumptions being observed to be contradicted by the data, the decision is taken to reconstruct the conditional VECM. By virtue of interpreting both the real exchange rate and the real wage as weakly exogenous variables, the revised model consists of merely two equations for $\Delta PINF_t$ and $\Delta LTIR_t$. For clarification, these two

[247] When the sample period does not include observations on the dependent variable from 1979q1 to 1979q3, the sums of the estimates of the coefficients which are attached to the lags on SOPI and W*SOPI are -0.0056 and 0.0031, respectively.
[248] In this section, only the key findings are made explicit. Full results are obtainable, upon request, from the author.

short-run functions include, as regressors, Δlog.$(RW)_t$ and Δlog.$(REER)_t$, in additions to the variables that were mentioned in section 6.5 of this chapter.

For the sake of brevity, consideration is given to merely the results which are obtained from the application of 3SLS estimation to the parsimonious version of the structural VECM.[249] In particular, the focus of attention is upon the estimated relationship between each of the two endogenous variables and the oil price measures.

With reference to the equation for $\Delta PINF_t$, the sums of the estimated coefficients which are attached to Δlog.(ROILP) and W*Δlog.(ROILP) are 5.8378 and -4.9397, respectively. Hence, the findings are broadly the same as earlier. However, the implication of the current estimates is that exports of oil would need to exceed consumption by eighteen per cent in order for a change in Δlog.(ROILP) to have no impact upon ΔPINF.

Regarding the equation for $\Delta LTIR_t$, the sums of the estimated coefficients which are connected to Δlog.(ROILP) and W*Δlog.(ROILP) are 1.4190 and -0.7860, respectively. These values are similar to those which were reported in Table 6.5.2 and imply that it would require the U.K.'s exports of crude oil to be approaching almost double its consumption of this commodity for the long-term interest rate to be insensitive to oil price developments.

[249] The results which are generated by *EViews*, when performing system chi-square tests, give no indication of the error terms in the model being autocorrelated.

On account of their change of status, it is necessary to construct marginal equations for Δlog.$(RW)_t$ and Δlog.$(REER)_t$.[250] With respect to each regression function, a general-to-specific modelling strategy is implemented for the purpose of achieving a parsimonious representation. Neither of the final equations is found to be associated with diagnostic problems.

Through undertaking analysis in this different context, a significant short-run relationship emerges between the real effective exchange rate and the real price of oil. In particular, within the equation for Δlog.$(REER)_t$, the sums of the estimated coefficients which correspond to Δlog.(ROILP) and W*Δlog.(ROILP) are 0.0524 and -0.0621, respectively.

With reference to the equation for Δlog.$(RW)_t$, the same as was seen in Table 6.5.2, an increase in Δlog.(ROILP) appears to benefit the growth of the real wage. However, the extent of the positive effect diminishes as exports of oil rise, relative to consumption. On this occasion, the sums of the estimated coefficients which are associated with Δlog.(ROILP) and W*Δlog.(ROILP) are 0.0329 and -0.0362, respectively.

6.8 Summary

In this chapter, the objective has been to implement the methodology which was outlined in Chapter Five. The first step consisted of performing a cointegration analysis, which involved applying in different contexts the trace and maximum

[250] These equations correspond to the specifications entering the extended linear VAR model.

eigen-value tests that had been proposed by Johansen. In spite of a desire to adopt a predominantly objective approach towards establishing the number of cointegrating vectors, ultimately, in order to ensure progress, a contribution was permitted from economic theory. The verdict that was eventually reached was the existence of two equilibrium relationships, which were given the interpretation of long-run equations for the real effective exchange rate and the long-term rate of interest.

The associated disequilibrium terms were employed to supplement the equations which had entered the extended linear VAR model. Following estimation and statistical testing, the two oil price variables and the short-run rate of interest were immediately recognised as being weakly exogenous. With respect to G.D.P., a post-sample analysis revealed that biased forecasts followed from allowing output to respond to situations of disequilibrium. Indeed, on the basis of a test of equal forecast accuracy, the conclusion was reached that the short-run behaviour of G.D.P. was more suitably described by, from earlier, the extended asymmetric equation than an error-correction function.

Likewise, for consumer price inflation, a comparison of actual and predicted values over the interval, 2005q2-2008q1, indicated the inadequacy of a representation which accommodated both of the disequilibrium variables. On this occasion, though, it was possible to eliminate bias by excluding the disequilibrium term which corresponded to the long-run equation for the exchange rate. Hence, there was a justification for the empirical investigation to proceed without the need to restrict price inflation to being weakly exogenous.

A conditional VECM was constructed and estimated, containing short-run equations for price inflation, the long-run rate of interest, the real wage and the real effective exchange rate. A parsimonious version of this model was achieved, following which a structural VECM was created that permitted contemporaneous relationships between the four endogenous variables. Application of 3SLS estimation showed each of price inflation, the long-term rate of interest and the real wage to be influenced significantly and positively by an oil price shock. However, for all three variables, the effect of the oil price change was lessened by an increase in the ratio of exports to consumption of crude oil. Indeed, for both price inflation and the real wage, the impact was seen to be negative in the situation in which the volume of exports matched the consumption of crude oil. By way of a contrast, it was inferred that, over the short run, the real effective exchange did not respond to a movement in the real price of oil.

For the reason that, within the context of the parsimonious structural VECM, neither the real wage nor the real effective exchange rate was found to react in a significant manner to either type of disequilibrium, the decision was taken to repeat the analysis on the basis of all of the variables being weakly exogenous, with the exception of consumer price inflation and the long-term rate of interest.

The relationships which emerged from estimation of the simultaneous-equations system were broadly the same as before, with an oil price development exerting a positive effect on both variables, which diminished as the volume of exports became larger in comparison to the consumption of crude oil. On this occasion, though, it was discovered that exports would need to exceed consumption by eighteen (eighty) per cent for price inflation (the long-term rate of interest) to be undisturbed by an oil price shock.

An attempt was also made to produce parsimonious specifications for the weakly exogenous variables. Having been accorded a change of status, the real effective exchange rate was subsequently found to be significantly dependent upon the real price of oil. Of particular interest was the short-run behaviour of economic activity. It may be recalled that an asymmetric function had been preferred for describing Δlog.(GDP). From the sequential application of exclusion tests, there was inferred no role at all for decreases in the real price of oil. In contrast, an increase in the real price of oil was calculated to have a negative effect on output growth, which declined as the volume of exports approached the magnitude of the consumption of crude oil.

CHAPTER SEVEN

CONCLUSION

The purpose of this thesis has been to perform an econometric investigation of the relationship between the price of oil and macroeconomic performance in the U.K.. The possible connection between movements in the price of oil and the behaviour of key macroeconomic indicators has been explored in the past, using time-series data on different countries. Analyses have been conducted which have been founded upon structural macroeconomic models. Studies have also been undertaken which have relied upon more of an atheoretical approach, estimating either individual equations or a VAR model.

Within the empirical literature, considerable emphasis has been given to the question of whether or not the macroeconomic effects of an increase and a decrease in the price of oil are asymmetrical. Interest in this subject would seem to have been derived from the existence of various theoretical explanations for why the extent to which an industrialised economy suffers from an oil price rise should exceed the degree to which it benefits from an oil price fall. In contrast, insufficient attention appears to have been paid to the issue of the consequences of a change in the price of oil being subject to variation over time. With respect to the U.K., two major developments have occurred over the past forty years which encourage the view that the macroeconomy should have become more robust to an oil price shock. Firstly, in the 1980s, the U.K. came to assume the status of a significant producer and exporter of crude oil. Secondly, there has taken place a progressive decline in the intensity with which crude oil is used in production. It should be appreciated that a failure to recognise the impact of these economic advancements may result in spurious econometric findings being obtained.

Within Chapter Three, a preference was exhibited for employing a VAR model as a framework for analysis, in order to limit the role that was played by economic theory towards establishing relationships. Subsequently, in Chapter Four, reliance was placed upon two systems that had featured in the study by Jimenez-Rodriguez and Sanchez (2005). The first of these was a linear specification, while the second incorporated separately unanticipated increases and decreases in the real price of oil, which had been suitably deflated by a measure of volatility. Extended versions of these two models were then created by applying multiplicatively to the oil price variables a weight which was formed by dividing the U.K.'s exports of crude oil by its consumption of this commodity.

Following OLS estimation, having assembled quarterly time series from 1972 to 2005, each of the four systems was used as a basis for conducting Granger-causality tests and undertaking innovation accounting. For the purpose of comparing the performances of the different models, consideration was given to their capability of explaining both within- and post-sample data on the relevant endogenous variables. Additionally, it was regarded as appropriate to examine the fit that was achieved of the data over a restricted sample period, having observed a change in the characteristics of some of the time series from the early 1980s.

Having conducted analysis in association with the linear VAR model, there was obtained scant evidence of any relationship between the real price of crude oil and the U.K. macroeconomy. The issue of the adequacy of the specification was raised by the finding that, for five of the seven endogenous variables, a value of a measure of goodness of fit could be markedly improved upon by ignoring data prior to 1982. However, it was recognised that, for both the change in price inflation and the growth in G.D.P., extraordinary events in 1979 contributed towards the attainment of a relatively low value of the coefficient of determination.

Through allowing for asymmetry, a slightly stronger connection between the price of oil and the U.K. macroeconomy was established. In particular, the within-sample evidence indicated a Granger-causal influence of oil price changes on consumer price inflation. Additionally, the results of block-exogeneity tests and the estimates of impulse responses showed increases in the real price of oil to be of greater relevance than decreases. Furthermore, in conducting a post-sample analysis over the period, 2005q2-2008q1, forecasts of the first-difference of the long-term rate of interest that were produced by the asymmetric model were inferred as having greater information content than those which emanated from the linear model.

In moving from the linear to the asymmetric VAR system, in general, only modest gains were observed in the fit of the data on the macroeconomic variables, irrespective of whether the sample period commenced in 1973/1974 or 1982. The validity of the asymmetric specification was also placed in doubt by the relatively poor predictions that were generated of the change in the rate of price inflation between 2005 and 2008.

When the linear VAR model was augmented to permit the macroeconomic effects of an oil price shock to be dependent upon the ratio of the U.K.'s exports to its consumption of crude oil, the earlier impressions of the (lack of) importance of oil price developments to macroeconomic performance were substantially altered. At the five per cent level of significance, the data supported the existence of Granger-causality extending from the real price of oil to each of the real wage, consumer price inflation and the short- and long-term rates of interest. Also, the forecast error variance decompositions signified that collectively the two oil price variables were capable of accounting for more than ten per cent of the variation in both ΔPINF and ΔLTIR. Furthermore, the post-sample analysis which was undertaken showed that the adaptation that had been applied to the linear VAR model was successful in delivering superior forecasts of the growth of G.D.P. and the change in price inflation.

Thus, the empirical evidence enables the conclusion to be drawn that, by virtue of ignoring the possible impact of fundamental shifts in the U.K.'s exports and consumption of petroleum, a risk is incurred of an underestimating the historical significance for the macroeconomy of disturbances to the real price of oil. In comparison to the original VAR system, for all variables, the extended linear model supplied a markedly superior fit of the within-sample data. Also, in some respects, it was associated with a greater degree of temporal stability, even though there could be observed an inconsistency over different time periods in the ability to explain the behaviour of the real exchange rate.

The extension that was applied to the asymmetric model also succeeded in raising the profile of the price of oil in relation to U.K. macroeconomic performance. Furthermore, it served to heighten awareness of the contrasting degrees of influence of increases and decreases in the real price of oil. As shown by the forecast error variance decompositions, collectively the oil price variables within this system were able to account for more than fifteen per cent of the fluctuations in four of the macroeconomic variables. Moreover, from the implementation of exclusion tests, it was possible to infer that five of the macroeconomic indicators were Granger-caused by oil price rises, while only one of these was found to respond significantly to earlier price reductions.

The results of the empirical analysis involving unrestricted VAR models suggested that, in order to acquire a fuller appreciation of the relationship between the price of oil and macroeconomic activity in the U.K., it is necessary to construct a model which allows for not only asymmetry but also the reaction to an oil price shock to be dependent upon structural changes in the economy. Adopting the framework of the extended asymmetric VAR system, it was possible to achieve not only an improvement in the explanation of the within-sample variation in the growth of G.D.P. but also predictions of the latter which were regarded as possessing greater information content than those that had been generated by the extended linear model.

Within Chapter Five, it was commented that a standard VAR model can be viewed as an underspecification on the basis that it ignores relationships between the respective variables pertaining to the long run. An improvement is considered to be a VECM which embeds long-run restrictions within a short-run system. In particular, within a

VECM, each of the endogenous variables is permitted to respond systematically to one or more types of disequilibrium.

Consequently, in Chapter Six, a cointegration analysis was undertaken with the objective of establishing long-run, equilibrium relationships. On the basis of the results which had been reported in Chapter Four, it was deemed to be essential to adopt as a framework a VAR model which allowed for the effects of a change in the real price of oil to vary in accordance with developments to the U.K.'s exports and consumption of crude oil.

Ultimately, two cointegrating equations were identified, which were interpreted as functions which were suitable for describing the long-run behaviour of the real effective exchange rate and the long-term rate of interest. The equation for log.(REER) showed a negative correlation between movements in the exchange rate and the real price of oil. However, as the ratio of the U.K.'s exports to its consumption of crude oil increased, this connection was seen to diminish. Indeed, in the situation in which, in quantity terms, exports surpassed seventy-six per cent of consumption (as was the case between 1982q1 and 1988q4 and over the interval, 1993q3-2004q3), the equation indicated a positive association between the two variables.

From the equation for the long-term rate of interest, there was evidence of positive long-run relationship between LTIR and log.(ROILP). The strength of the tie that existed between the two variables was weakened by a rise in the ratio of the U.K.'s exports to its consumption of crude oil. However, on this occasion, the implication of the respective estimates was that exports would need to be more than 1.7 times the size of consumption to produce a negative correspondence.[251]

Both within- and post-sample evidence was accumulated in an attempt to establish whether or not the short-run behaviour of a variable entering the analysis is influenced by situations of long-run disequilibria. Initially, for the purpose of constructing a conditional VECM, four variables were interpreted as weakly exogenous. However, during the course of progressing towards a parsimonious structural VECM, a further two variables were recognised as being statistically unresponsive to deviations of the exchange rate and the long-term rate of interest from their respective long-run paths.

The two equations which ultimately comprised the structural VECM related to the long-term rate of interest and consumer price inflation. The application of sequential testing enabled a parsimonious version of the model to be achieved. From the estimates which were reported in section 6.7, the inference was drawn that a change in Δlog.(ROILP) stimulates a short-term movement in both ΔPINF and ΔLTIR in the same direction. However, as the ratio of the U.K.'s exports to its consumption of crude oil rises, the extent of these responses diminishes. On the basis of the respective estimates, though, it would be necessary for the volume of exports relative to consumption to exceed by a significant margin its historical maximum for an oil price shock to be of no consequence for both ΔPINF and ΔLTIR.

[251] Recall that the maximum value of the ratio of exports to consumption of crude oil was 1.18 (in 2000q2).

The implementation of a general-to-specific modelling strategy also enabled parsimonious equations to be obtained for the six weakly exogenous variables. The implication of the estimated equation for Δlog.(GDP) was that decreases in the real price of oil are of no relevance for determining the growth of output. Although unanticipated increases in the real price of oil were seen to be influential, their negative effect on economic activity was suppressed by a rise in the ratio of exports to consumption of crude oil.

The suggestion of the final equation for ΔTB was that, prior to the U.K. acquiring the status of an exporter of oil, the reaction to an oil price hike had tended to be the implementation of an expansionary monetary policy. However, when exports represented more than ninety-seven per cent of consumption of crude oil, the nature of the response altered to being contractionary.

The parsimonious equation for the real effective exchange rate showed a positive dependence of Δlog.(REER) on changes in output growth and the short-term rate of interest, which is consistent with standard theory. In contrast, the estimated relationships between Δlog.(REER) and each of Δlog.(ROILP) and W*Δlog.(ROILP) appeared perverse and would possibly be considered to be spurious.

Finally, the estimated marginal equation that was eventually established for the real price of oil indicated a remarkable sensitivity of Δlog.(ROILP) to past changes in Δlog.(GDP). However, the magnitude of the respective estimate was discovered to be founded upon matching extreme observations on the two variables relating to a single quarter, 1974q1. Following the exclusion of this period from the analysis, the consequence of an increase or decrease in U.K. output growth for Δlog.(ROILP) became negligible from a statistical perspective.

Thus, from the summary which has been provided above, a general conclusion that can be reached from the empirical investigation that has been conducted in this thesis is that movements in the price of oil have been of relevance for the performance of the U.K. macroeconomy since the early 1970s. Indeed, overall, an unexpected increase in the price of oil has been seen to be harmful for economic growth. In this respect, the outcome of this research effort would appear to be broadly in line with the findings that have been achieved from earlier studies involving U.K. data, e.g., Mork *et al*. (1994), Bjornland (1998, 2000) and Cunado and Perez de Gracia (2003). However, a supplementary result that has been obtained is that, as the ratio of the U.K.'s exports of crude oil to its consumption of this commodity has risen, the extent of the influence of an oil price shock on the macroeconomy has declined. The failure to allow for the consequences of structural adjustments to the U.K. economy possibly contributed towards Jimenez-Rodriguez and Sanchez (2005) being unable to find significant evidence of G.D.P. being Granger-caused by the real price of oil in any context.[252] Within Chapter Four of this document, it was demonstrated that, by virtue of applying a suitable weight to the scaled measures, SOPI and SOPD, statistically far stronger results could be produced and a clearer distinction could be drawn between the effects of unanticipated increases and decreases in the real price of oil upon economic activity.[253]

[252] See the penultimate row in Table 2 (p. 210) of the article by Jimenez-Rodriguez and Sanchez (2005).
[253] See Table 4.9.3.1 in Chapter 4.

It must be respected that, in undertaking any empirical study, there is a need to be mindful of the limitations of the investigation that has been performed and the scope for further research in the subject area. A key decision that was taken in Chapter Three of this thesis was the framework to use for analysis. It may be recollected that the linear and asymmetric VAR models which were adopted represented systems which had been constructed by Jimenez-Rodriguez and Sanchez (2005) when conducting an earlier multi-country study. These models have the potential be criticised for only providing a partial description of the behaviour of an open economy. In particular, they may be regarded as deficient in terms of failing to incorporate a measure of world output or an indication of monetary conditions outside of the domestic economy.

It may also be construed as being inadequate to allow for movements in the price of only one essential commodity to impact upon U.K. macroeconomic performance. In generating empirical results, what appeared to be an anomaly was the strong statistical support for asymmetric effects of increases and decreases in the real price of oil on ΔPINF that was derived from the within-sample data, which was unable to be replicated following an examination of the post-sample data. The possibility exists that the relatively poor forecasts that were produced by the asymmetric equations are the consequence of an underspecification. Although the selected VAR models incorporated the price of oil, they excluded the prices of other key inputs which would not have necessarily exhibited the same type of behaviour over the interval of interest. More specifically, between 2005q1 (the end date of the estimation period) and 2008q1 (the final date of the prediction period), the price of Brent crude oil rose by almost 103 per cent, which compares with a figure of only 63 per cent for an index of non-fuel commodity prices.[254]

Throughout the empirical analysis, the task of comparing the performances of different models has been handicapped by distortions to the time series on U.K. G.D.P. which were caused by the frequent occurrence of industrial action in the 1970s. Indeed, the impact on the data of strike activity and working to rule possibly contributed towards the failure to be able to admit a disequilibrium term to the short-run equation for Δlog.(GDP). Within this thesis, there has been a general reluctance to represent what are regarded as extraordinary events by dummy variables, believing such a strategy to be inappropriate when a system has been constructed which allows for dynamic interrelationships between the respective variables. However, in order to raise the level of confidence in the results which are obtained, consideration should be given to the addition to a model of a variable that seeks to signify directly labour disputes. An alternative approach, though, is to reject G.D.P. as the output measure, replacing this by a variable which exhibits less sensitivity to an episode of industrial action. The rate of unemployment would seem to be a suitable candidate and, indeed, has featured in earlier analyses (e.g., Hamilton (1983)).

It should be appreciated, though, that the consequence of applying any of the extensions which have been suggested above would most likely be an expansion of the size of the VAR model in terms of its number of parameters. In constructing such a system, there is a reluctance to accommodate a large number of variables on

[254] This calculation was performed using quarterly data which were accessed on-line from the I.M.F. publication, *International Financial Statistics*, on 12th September 2012.

account of the implications for the degrees of freedom and the clarity of the estimates. As has been seen, the most developed VAR model in this thesis already incorporates ten endogenous variables. Thus, serious consideration needs to be given to the merits of entering additional factors before any further augmentation is attempted.

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