Essays on Macroeconomic Fluctuations and International Capital Mobility

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Abstract

This dissertation consists of four essays. The first two essays investigate macroeconomic fluctuations and their sources. The third and fourth essays examine international capital mobility.

In the first essay I deal with two interrelated issues of empirical macroeconomics. First, I examine the long-run comovement between sectoral outputs in the US economy. I perform a decomposition of sectoral outputs into permanent and transitory components and then examine the importance of innovations to both of these components. Second, I provide evidence concerning the sources of permanent innovations in the economy. The disaggregated framework enables me to identify not only whether the shocks are permanent or transitory, but enables me also to investigate the relationships between these shocks and other macroeconomic variables.

The second essay examines the sensitivity of output fluctuations to different decomposition techniques. Typical analyses of fluctuations decompose output into a permanent and a transitory component and examine their characteristics at different frequencies. Since there is no consensus on how to subtract cycle from trend, different conclusions have been reached on the properties of both components. Using seven different procedures I decompose output and compare sample moments of long- and short-

run fluctuations in output and persistence of shocks to both components. The results show that there are significant differences across techniques.

The third and fourth essays investigate whether the high saving-investment correlation observed in cross-country regressions constitutes a robust empirical regularity. The high saving-investment link has been interpreted by some authors as evidence that world capital markets are not integrated. I reexamine the long-run saving-investment relationship across OECD countries using cointegration methods. This econometric approach enables one to provide evidence regarding the saving-investment link at a disaggregated level, namely, for each country separately and accounts for the nonstationarity of the underlying time series. Contrary to the conclusions of previous studies, my results indicate that long-term capital is internationally mobile for most OECD countries, especially during the flexible exchange-rate period.

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This thesis is dedicated to all past and present inhabitants of Planet Earth and among them especially to my late father. If it were not for him and the rest of them, no word could be said or written. Thanks folks!

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"I'm not Sherlock Holmes or Philo Vance. I don't expect to go over ground the police have covered and pick up a pen point and build a case from it....It's not things like that they overlook if they overlook anything. I'm not saying they often overlook anything when they're really allowed to work. But if they do, it's apt to be something looser and vaguer..."

Philip Marlowe, The Big Sleep by R.T. Chandler, 1967.

Essay 1:

Sectoral Shocks and Aggregate Fluctuations:

A Common Factor Analysis for the US Economy

Abstract

In this paper I deal with two interrelated issues of empirical macroeconomics. First, I examine the long-run comovement between sectoral outputs in the US economy. I perform a decomposition of sectoral outputs into permanent and transitory components and then I examine the importance of innovations to both of these components. I also attempt to draw conclusions for aggregate output. Second, I provide evidence concerning the sources of permanent innovations in the economy. The disaggregated framework and the common factor analysis enable me to identify not only whether the shocks are permanent or transitory, but enable me also to investigate the relationships between these shocks and other macroeconomic variables. I claim that this feature of our analysis allows one to more clearly identify the sources of these shocks.

I. Introduction

One of the most important findings in empirical macroeconomics during the 1980s has been that many aggregate macroeconomic variables contain unit roots. This discovery has changed the way in which economists think about macroeconomic fluctuations. The traditional approach to macroeconomic fluctuations assumed a deterministic trend in aggregate variables and attributed the observed fluctuations around this trend to temporary disturbances bearing no consequences for the behavior of the economy in the long-run. Starting with the seminal paper by Nelson and Plosser (1982), however, a large number of studies have shown that many components of economic activity contain a unit root or a stochastic trend so that contemporary events have permanent effects on the long-run behavior of the economy. The finding of unit roots was thus inconsistent with the traditional approach to business cycle analysis.

This fact gave rise to a new set of theoretical as well as empirical models of fluctuations, known as real business cycle models. These models claim that a common stochastic trend which represents the cumulative effect of permanent shocks to productivity explains much of the variation in aggregate variables. In extreme versions of these models, such as Long and Plosser (1983) and Prescott (1986), all the variation in output is attributed to real factors. In contrast to traditional analyses, these models imply that all shocks have permanent effects on the economy. Therefore if the hypothesis that there is only one type of disturbance is true, there would not be any distinction between short- and long-run dynamics of the economy and the analysis would be straightforward. Nonetheless, real business cycle models are not restricted to have a single shock and if the economy is subject to more than one type of innovation, as is likely, then the distinction between permanent and transitory components of economic activity continues to be important.

Though important, it is not trivial to identify permanent and transitory components of real activity. In the last ten years several attempts have been made to decompose aggregate output. At first, researchers used univariate techniques to achieve a desired decomposition. While Beveridge and Nelson (1981) assumed that the innovations to both components are perfectly correlated and therefore there is only a single shock, Watson (1986), at the other extreme, assumed them to be totally uncorrelated. Both approaches were criticized for being incompatible with certain models of fluctuations (Christiano and Eichenbaum (1989)) and for suffering econometric shortcomings (Quah(1990)). Consequently, a new wave of research emerged where a multivariate approach has been considered. These models are semi-structural in the sense that they do not constrain the process generating the permanent components of the variables. Instead, they use information in macroeconomic variables other than output, and identify permanent and temporary shocks by imposing restrictions on the structural representation of the multivariate output generating process, that is imposing restrictions on the long-run impact of different innovations and the correlation among them. In the well-known study by Blanchard and Quah (1989), for example, the stationary unemployment rate is used along with aggregate output to assess the importance of permanent and temporary movements in the economy. Specifically, they assume that the innovations to the stationary unemployment rate do not affect both variables in the long-run whereas innovations to output are assumed to have a long-run impact on output. Meanwhile, King et al. (1991) uses a long-run restriction in a vector error-correction model which involves output, consumption, and investment. They base their restriction on the implication of a large class of real business cycle models that the shocks to the common stochastic trend in these variables are permanent productivity shocks.

While empirical macroeconomists are trying to distinguish permanent shocks from temporary ones, there is still controversy about what these shocks really are. Blanchard and Quah (1989) interpret permanent disturbances as supply shocks and temporary disturbances as demand shocks. Real business cycle models assert that all permanent changes in macroeconomic variables are due to productivity changes. This technology interpretation of observed unit roots in aggregate variables has been criticized by several researchers. Durlauf (1989), for example, using international and intersectoral outputs and bivariate cointegration analysis drew the conclusion that it is difficult to interpret stochastic trends in real activity as an outcome of technological changes. Later, Evans (1992) analyzed the exogeneity of productivity shocks and found that several policy variables are able to explain variation in the Solow residuals. The emphasis in these studies was that endogeneity of productivity and externalities in the economy may allow shifts in aggregate demand to have effects on the economy in the long-run. Therefore, it is important not only to distinguish between permanent and transitory components of economic activity, but also to identify the sources of the economy's dynamics in order to draw conclusions about the behavior of the economy.

In this paper we follow the tradition of multivariate approach and employ a fairly new econometric technique, the common factor analysis of Gonzalo and Granger (1991), using sectoral outputs to provide evidence for two interrelated questions. First we investigate the importance of permanent and transitory components obtained for sectoral outputs using common factor analysis. Since sectoral outputs add up to gross domestic product we also attempt to draw conclusions for aggregate output. Second we investigate possible associations between the common factors and other variables in the economy.

We argue that the information contained in the relations among sectoral outputs enables us to obtain more precise estimates of permanent and temporary factors in the economy through the disaggregated model than can be obtained by a direct analysis of aggregate series. By using cointegration analysis and imposing necessary long-run restrictions we achieve a permanent and transitory decomposition of sectoral outputs which we consider more appealing than those provided in the literature. Then we investigate the relation between these components as well as the relative importance of the innovations to both of them.

Later, we go one step further and attempt to provide evidence concerning the sources of permanent innovations in the economy. The disaggregated framework and the common factor analysis enable us to identify not only whether the shocks are permanent or transitory, but enable us also to investigate the relationships between these factors and other macroeconomic variables. This feature of our analysis allows us to 'validate and refine [the] identification of shocks as supply and demand shocks' (Blanchard and Quah (1989)).

The plan of the paper is as follows: In the next section the Gonzalo-Granger common factor analysis and the testing methodology are described. In the third section we report empirical findings. First we discuss the comovement in sectoral outputs. Then we investigate the permanent and transitory components of sectoral outputs and measure their relative importance. The fourth section analyzes the nature of these common factors. Section five concludes.

II. Econometric Methodology

This section provides an overview of the estimation of cointegration relationships among sectoral outputs and the identification of the common factors determining those relationships. Cointegration among variables, interpreted as long-run equilibrium relationships tying individual variables together, has received a great deal of attention in last few years while much less work has been done concerning common factors. However, these factors are important as being the driving forces which result in cointegration. Also, their nature and relationships with other variables may provide valuable information for economic theory and policy making. Moreover, the common factor analysis of Gonzalo and Granger (1991) that we employ here has the advantage of inherently decomposing output series into a permanent and a transitory component, each of which conveys different kinds of information. Hence, the estimation of the common factors in the system and the decomposition obtained have certain characteristics which can be exploited to understand the nature and sources of fluctuations in the US economy.

Cointegration and Common Factors

Consider the following model:

Let X_t be a p-vector of sectoral outputs integrated of order one, I(1), and suppose that the time series properties of X_t can be represented by a finite order vector autoregression (VAR) model with Gaussian errors. Then,

$$X_t = \Pi_1 X_{t-1} + \dots + \Pi_k X_{t-k} + \mu_0 + \mu_1 t + \varepsilon_t \tag{1}$$

or equivalently,

$$\Delta X_t = \Gamma_1 \Delta X_{t-1} + \dots + \Gamma_{k-1} \Delta X_{t-k+1} + \Pi X_{t-k} + \mu_0 + \mu_1 t + \varepsilon_t \tag{2}$$

where μ_0 and μ_1 are constants, Δ is the first-difference operator, ε_t is a vector of serially uncorrelated disturbances,

$$\Gamma_i = -(I - \Pi_1 - \dots - \Pi_i) \quad \text{for } i=1,\dots,k-1, \text{ and}$$

$$\Pi = -(I - \Pi_1 - \dots - \Pi_k).$$

The coefficient matrix Π contains the information about long-run relationships in the data. Two possible extreme cases where the rank of Π is zero or p are trivial. In the first case, the model (Equation (2)) corresponds to traditional differenced vector autoregressive system and in the second, it is implied that the variables in the system are stationary. The interesting possibility is that if the rank of Π is r where $0<r<p$. In this case the long-run multiplier matrix, Π, can be decomposed into:

$$\Pi = \alpha\beta' \qquad \textbf{(3)}$$

where β is the (r x p) matrix of cointegrating vectors and α is the (p x r) adjustment coefficient matrix. Consequently, $\beta' X_t$ forms r time series with integration of order zero which are interpreted as the long-run equilibrium relations between the variables in vector X_t (Johansen (1988,1991a) and Johansen and Juselius (1990)).

To close the system, then there has to be $m = p - r$ I(1) common factors as proved by Stock and Watson (1988). Hence the process X_t can be rewritten as:

$$X_t = A_1 f_t + A_2 z_t \qquad (4)$$

where f_t is (m x 1) common factor matrix, $z_t = \beta' X_t$ and A_1 and A_2 are loading matrices. Once the rank of cointegration matrix, Π, is estimated then the only unknown in Equation (4) is f_t since A_1 will be any basis of the null space of β'. Gonzalo and Granger (1991) suggest following two conditions to identify the common factor matrix, f_t. First they impose the elements of f_t to be linear combinations of the variables in the system. The second condition requires $A_1 f_t$ and $A_2 z_t$ to form permanent and transitory components of X_t, respectively according to the following definition:

Definition: Let X_t be a difference stationary sequence. A permanent-transitory decomposition for X_t is a pair of stochastic processes P_t and T_t, such that

(i) P_t is difference stationary and T_t is covariance stationary

(ii) $Var(\Delta P_t) > 0$ and $var(T_t) > 0$

(iii) $X_t = P_t + T_t$

(iv) $\lim_{h\to\infty} \frac{\partial E_t(X_{t+h})}{\partial \varepsilon_{P_t}} \neq 0$ and

$\lim_{h\to\infty} \frac{\partial E_t(X_{t+h})}{\partial \varepsilon_{T_t}} = 0$

where E_t is the conditional expectation with respect to the past history, and ε_{P_t} (ε_{T_t}) is the part of innovations in P_t (T_t) that is orthogonal to the innovations in T_t (P_t).

Once these conditions have been met, then the common factors can be easily estimated from the vector error correction model (VECM) (2) as

$$f_t = \alpha_\perp' X_t \tag{5}$$

where $\alpha_\perp$ is (m x p) and $\alpha_\perp' \alpha = 0$.

There are certain features in the Gonzalo-Granger common factor model and their decomposition which require special attention. Most decomposition methods commonly used in the literature are univariate. Here, however, we utilize information in all sectoral outputs to analyze both the long-run and short-run dynamics of the economy. The identification of the common factors is achieved differently than the univariate decomposition methods where they impose the condition that the permanent component be a random walk, or require the two components to be orthogonal at all leads and lags. By imposing the condition that the common factors are linear combinations of the variables in the system, we enable us to express common factors as observable so that we can analyze their nature and perform hypothesis testing on them. The second condition that $A_1 f_t$ and $A_2 z_t$ to form permanent and transitory components, on the other hand, insures that the only shocks which have a permanent effect can come only from the innovations to the permanent component. Therefore they summarize long-run behavior of the variables in the system.

Further, the trend-cycle decomposition of time series using common factor analysis is comparable to the existing methods, in the sense that the common trends of Stock and Watson (1988) decomposition is the random walk components of the elements of the common factor matrix, f_t. Similarly, the decomposition that requires orthogonality between permanent and transitory components can be obtained from the analysis, at the expense of forming the common factors as linear combinations of future, present and past values of X_t. The analysis we employ here also has some resemblance to the special trend-cycle decomposition developed by Vahid and Engle (1992) based on the common features analysis of Engle and Kozicki (1990). Their decomposition is possible when there are enough short- and long-run restrictions. That is, they require that the sum of the rank of the common features (the sum of cointegrating and cofeature rank) to be equal to the number of the variables in the system. Nonetheless, such restrictions are not always available and this special decomposition cannot be achieved all the time. However, such strong restrictions are not necessary for our analysis whereas the same properties as Vahid and Engle's decomposition are maintained.

The common factor analysis also enables one to analyze large systems by successive reductions. Systems with a large number of variables can be very difficult to interpret. For example, in the case of this paper, the system consists of sectoral outputs and other variables which are considered as potential sources of persistence would be excessively complex. However, we can partition the system into blocks such that first we analyze the common features of sectoral outputs, then relate the common factors of this smaller system to other variables that we assume move together or drive these factors.

Finally, the factor model meets standard assumptions of factor analysis. The common factors are not cointegrated (i.e., factors are uncorrelated) and the changes in common factors are orthogonal to $A_2 z_t$, i.e., $cov(\Delta f_t, z_t \mid lags(\Delta X_{t-1})) = 0$. Nevertheless, changes in the permanent component are allowed to affect the transitory component and also, changes in the transitory component can have an impact on the changes of permanent component.

Estimation and Hypothesis Testing

Although the techniques used to estimate cointegration properties of time series are familiar, to motivate the estimation of the common factors and to introduce notation a brief review is in order.

The cointegrating matrix β, as has been shown by Johansen (1988,1991a) and Johansen and Juselius (1990), can be estimated as the eigenvectors associated with the r largest, statistically significant eigenvalues of the following equation:

$$| \lambda S_{kk} - S_{ko} S_{oo}^{-1} S_{ok} | = 0 \tag{6}$$

where S_{oo} and S_{kk} are the residual moment matrices from the least square regressions of ΔX_t and X_{t-1} on $\Delta X_{t-1}, ..., \Delta X_{t-k+1}$, respectively, and S_{ok} is the cross-product moment matrix of the residuals. The maximized likelihood function is given by:

$$L_{max}^{-2/T} = | S_{oo} | \prod_{i=1}^{r}(1-\hat{\lambda}_i) \tag{7}$$

where $\hat{\lambda}_i$ is the i^{th} largest eigenvalue of the Equation (6).[1]

The number of cointegrating vectors or the rank of Π matrix is determined by comparing the values of the likelihood function for the unrestricted model (r=p) and the restricted model ($r=r_0$). The resulting log-likelihood ratio is called the 'trace statistic' and is given by:

$$LR = \frac{T}{2} \sum_{i=r_0+1}^{p} \ln(1-\hat{\lambda}_i). \tag{8}$$

The distribution of the log-likelihood ratio test statistic is not given by the usual χ^2 distribution but rather a multivariate version of the Dickey-Fuller test statistic.[2]

The estimation of the common factors can be obtained in a similar way by imposing the identifying conditions, i.e., $f_t = B X_t$ and $z_t = \alpha' X_t$ has no long-run impact on X_t. First replace Π in Equation (2) with Equation (3). Then the linear combination that satisfies the second condition is $B = \alpha_{\perp}'$.

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[1] Hamilton (1994) provides a more detailed discussion and very useful insights for the full information estimation technique.

[2] A second test to determine the rank of Π matrix is to compare the likelihoods of restricted models $r=r_0$ and $r=r_0+1$. This statistic is called 'maximum eigenvalue statistics' and is given by $LR_{max} = \frac{T}{2}\ln(1-\hat{\lambda}_i)$. However throughout this paper we will use the 'trace statistic'.

Under the hypothesis of cointegration, the maximum likelihood estimator of $\alpha_\perp$ can be found by solving the equation:

$$| \theta S_{oo} - S_{ok} S_{kk}^{-1} S_{ko} | = 0 \tag{9}$$

The choice of $\hat{\alpha}_\perp$ is the eigenvector associated with the m smallest eigenvalues, and the maximized likelihood function is given by:

$$L_{max}^{-2/T} = | S_{oo} - S_{ok} S_{kk}^{-1} S_{ko} | \prod_{i=r+1}^{p} [(1-\hat{\theta}_i)]^{-1}. \tag{10}$$

Usually economic theory implies certain long-run relations between variables. Johansen (1988) and Johansen and Juselius (1990) show how to estimate the cointegrating matrix under linear restrictions. A restriction on β can be formed as

$$\beta = H \varphi \tag{11}$$

where H is a (p x s) restriction matrix and φ is a (s x r) matrix of coefficients. Under this hypothesis the maximum likelihood estimator of φ can be found as the eigenvectors associated with the r largest, statistically significant eigenvalues of the equation:

$$| \tilde{\lambda} H' S_{kk} H - H' S_{ko} S_{oo}^{-1} S_{ok} H | = 0 \tag{12}$$

with the likelihood function:

$$L_{max}^{-2/T} = | S_{oo} | \prod_{i=1}^{r} (1-\tilde{\lambda}_i). \tag{13}$$

The likelihood ratio statistic of the hypothesis (11) in (3) is

$$T \sum_{i=1}^{r} \ln \frac{(1-\tilde{\lambda}_i)}{(1-\hat{\lambda}_i)} \tag{14}$$

and distributed as standard χ^2 with r (p - s) degrees of freedom.

Similarly restrictions on the common factors can be formed and tested. Let G be (p x n) restriction matrix and ϕ be (n x m). Then the hypotheses on $\alpha_{\perp}$ can be formed as:

$$\hat{\alpha}_{\perp} = G\,\phi. \tag{15}$$

The estimate of ϕ are the eigenvectors associated with the n smallest eigenvalues of the following problem:

$$|\,\theta\, G'\, S_{oo}\, G - G'\, S_{ok}\, S_{kk}^{-1} S_{ko}\, G\,| = 0 \tag{16}$$

with the likelihood function:

$$L_{max}^{-2/T} = |\, S_{oo} - S_{ok}\, S_{kk}^{-1}\, S_{ko}\,|\,\{\prod_{i=r+1}^{p}(1-\tilde{\theta}_{i+n-p})\}^{-1}. \tag{17}$$

The likelihood ratio statistic of the hypothesis (15) in (3) is given by:

$$T\sum_{i=r+1}^{p}\ln\frac{(1-\tilde{\theta}_{i+n-p})}{(1-\hat{\theta}_{i})} \tag{18}$$

and distributed again as standard χ^2 with (p - r) (p - n) degrees of freedom.

III. Empirical Evidence

The common factor analysis described in Section II is applied to logarithms of per capita real output for ten sectors of the post-war US economy. Data consist of quarterly observations and to avoid observations that occur during periods of price controls, the Korean War, and the Treasury-Fed accord the regressions are run over 1954:1 - 1991:4. The sectors are Agriculture, Forestry and Fishing (Agr), Mining (Min), Construction (Con), Durable Manufacturing (Dma), Non-durable Manufacturing (Ndm), Transportation and Communication (Tco), Electricity, Gas and Sanitary Services (Egs), Domestic Trade (Trd), Finance, Insurance and Real Estate Services (Fin) and Other Services (Ser) and they add up to private Gross Domestic Product. One concern of this paper is to provide some evidence for aggregate output by utilizing the information in sectors. Since the aggregate is the simple sum of the sectoral outputs, the sum of logarithms would not give the logarithm of the aggregate output. Therefore, we use the following approximation:

$$\Delta\log(Y_t) = \sum_i w_{it}\Delta\log(y_{it}) \tag{19}$$

where Y_t is the aggregate output, y_{it} is i^{th} sectoral output and w_{it} is defined as $w_{it}=0.5*(s_{it}+s_{it-1})$ with s_{it} being the share of sector i at time t. In the rest of this paper we use this new measure as real per capita gross domestic product (GDP).[3] The sources and details of the data are provided in the Appendix A.

Figure 1 presents shares of sectoral outputs in aggregate. We classified sectors as "goods" and "services".[4] The first group consists of Agr, Min, Con, Dma, Ndm and Egs whereas the latter group contains Tco, Trd, Fin and Ser. The share of service sector was 48% at the beginning of the sample which increased to 67% to the expense of goods sector. However, even within these groups sectoral shares follow different patterns. For example, within the service sector the shares of Fin and Ser increased drastically while the shares of Tco and Trd decreased throughout the observed period. Within the goods sector, on the other hand, shares of Agr, Min, Dma and Ndm decreased, the share of Egs

3 Pesaran et al. (1991) use unit weights. We prefer time varying weights since the shares of sectors are changing over time.

4 We have tried many different classifications to see if there is a certain pattern that can be attributed to some group of sectors. Unfortunately, such common characteristics were not available at this stage. In order not to bore the reader with excessive graphs and numbers we present only the division between "goods" and "service" sectors.

increased and share of Con did not show any significant change. This observed difference in the patterns of sectoral shares has two important implications. First, clearly there occurred some shifts in the composition of aggregate output. Second, there must be more than one and significantly different forces that drive sectoral outputs in the long-run in order to explain the observed difference in patterns. These two facts together imply that models where aggregate data are used and thereby only one driving force is assumed, are misspecified since these models are inadequate to capture the variety of dynamic behavior observed in the economy. Hence, the gain from a multisectoral model is expected to be significant.

Testing for Unit Roots in Sectoral Outputs

The VEC model we use here, requires, at least, some of the series to be I(1).[5] To establish this fact we run Augmented Dickey Fuller (ADF) tests for each of the sectoral outputs and their differences. The ADF specification allows a constant and a linear trend and the critical values for 1%, 5% and 10% significance levels are -4.02, -3.44 and -3.14, respectively. Table 1 presents the results of these tests for five different lag lengths over the sample period 1954:1-1991:3.

Evidence of unit roots in sectoral outputs has been shown by Durlauf (1989) and Pesaran et al. (1993) using annual data. The results obtained by using quarterly data is in line with the earlier tests. For all sectors we find unit roots at 1% significance level.

Finally, we check whether there exists a second unit root in sectoral outputs. The null hypothesis of a unit root in differences is rejected overwhelmingly for all sectors and

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[5] It is important to make sure that the series do not contain second unit roots. In that case the model has to be specified to take into account of various types of long-run relationships. For details, see Johansen (1991b).

the aggregate measure assuring that the series are I(1). We proceed with accepting only one unit root in the levels of all ten sectors and aggregate output.

Cointegration and Common Factor Analysis

Consequently to determine the cointegration relationships among sectoral outputs and to estimate common factors in the post war US economy, Johansen's maximum likelihood estimation procedure is applied. To estimate cointegration properties of the sectoral outputs, the VECM has been chosen so that each equation contains eight lags of levels of sectoral outputs. The asymptotic distribution of the test statistic to determine the rank of long-run multiplier matrix depends on the existence of deterministic variables in the error correction representation. As a first step we test whether the error correction representation of the system can be restricted to contain only linear trends. We used the Likelihood Ratio test obtained from the concentrated likelihood function, as suggested in Johansen (1991a). The statistic for this test is 53.31, which rejects the restriction on deterministic time trends and gives rise to a quadratic trend in the moving average representation of the system.[6] Hence we estimate the following equation:

$$\Delta X_t = \Gamma_1 \Delta X_{t-1} + \dots + \Gamma_{k-1} \Delta X_{t-k+1} + \Pi X_{t-k} + \mu_0 + \mu_1 t + \varepsilon_t \qquad (20)$$

Table 2 presents trace statistics and critical values for the specified model. Starting from the null that there exists at most one cointegrating relationship against the alternative that the long-run multiplier matrix has zero rank, and then by changing the null to that the rank of long-run multiplier matrix is r against the alternative of zero (for r=1,...,10), we conclude that there are seven cointegrating relationships among the sectoral outputs. Our finding that there is substantial degree of long-run comovement

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[6] The details of model selection are given in Appendix B.

among sectors is in line with Durlauf (1989) and Pesaran et al. (1993). In the literature two explanations are provided for this comovement of sectoral outputs. While one view argues that perfect correlation among productivity shocks to different sectors results in a smaller dimension of technology compared to the number of sectors, the other approach argues the existence of factors other than technology which drive the economy in the long-run and link sectoral outputs together. Yet at this stage, it is not identifiable which one of the two explanations fit to the data. We will come back to this question in the next section.

In order to complete the description of the data, we employ the common factor analysis and decompose each output into permanent (trend) and transitory (cycle) components. The estimates of the factor model are given in Table 3. Since Equation (19) defines the aggregate measure as a weighted sum of aggregate outputs, by applying the same weights to the components of sectoral outputs we obtained a special decomposition of the aggregate output as well.[7] In Table 4 the sample statistics are presented.[8] The reader should be warned that the means and variances of the original series and permanent components do not exist for they are non-stationary. Nevertheless, they are useful to provide some sense about the behavior of these series throughout the observed period. The surprising finding by Issler and Engle (1992) that the trends are more volatile than the series themselves is not supported by our analysis. The sample variances of sectoral outputs are not smaller than the sample variances of the permanent

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[7] The decomposition of aggregate output can be achieved in the following way:

$$\Delta \log(Y_t) = \sum w_{it} \Delta \log y_{it} = \sum w_{it} \Delta (P_{it} + T_{it}) = \sum w_{it} \Delta P_{it} + \sum w_{it} \Delta T_{it} = \Delta P_t^Y + \Delta T_t^Y$$

[8] Following the conventional approach we removed the deterministic parts from the transitory components and added these extra elements to the permanent component.

components. When we compare the changes in outputs and trends, we find that the growth outputs are more volatile than the growth of permanent components except four sectors, Min, Dma, Egs and Fin. We also find negative correlation between trends and cycles as in univariate decompositions as found in univariate applications of Beveridge and Nelson (1981). A similar result holds for aggregate output as well. The growth of aggregate output is twice more volatile than the growth of its permanent component while the change in the permanent component is significantly negatively correlated with the transitory component.

The cycles and trends in sectoral outputs and aggregate output are plotted in Figure 2 and Figure 3. Seven out of ten sectors more or less conform with the NBER dates for economic recessions. Agr, Egs and Ser are the three counter-cyclical sectors. Nevertheless, the amplitudes of the cycles are different with Agr, Min and Con having the highest. A striking characteristic of the transitory components are that the length of cycles from expansion to expansion or from contraction to contraction are around eight to ten years longer than the length of cycles in univariate analyses[9]. This is especially so for the transitory component of the aggregate output which also matches the NBER chronology.

A more important observation from these graphs is that the behavior of the permanent components are not similar during different designated NBER recessions. Unlike univariate analyses, permanent components we obtained do not show monotonic increases during recessions. For example, the permanent component of the aggregate output declines during the first three recessions, while the same cannot be said for the

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9 The usual length of cycles in Beveridge-Nelson decomposition is extremely short, one to three quarters. The longest cycles obtained by a univariate analysis are cycles of unobserved component models or some versions of Hodrick-Prescott filter where the length of a cycle is around four to six years.

latter ones. Moreover, there is no consistent pattern across sectors, that is, the behavior of the permanent component for each sector is different than the others during a given recession. Hence, we conclude that business cycles are not alike. The differences show themselves in two major ways. First, a recession can be completely due to transitory movements in the output, or it may be due to a negative change in the trend. Second, whether the recession is because of a cyclical downturn or a declining trend is different for each sector in the economy.

Importance and Persistence of Different Types of Shocks

In the literature, another concern has been the importance and the persistence of certain type of shocks to the economy. Blanchard and Quah (1989), using output and employment data in a structural VAR system, have examined the identification of permanent and temporary shocks and their effects on both variables. Similarly, King et al. (1991) used a structural VECM to quantify the persistence of what they call permanent productivity shocks. The identification of the shocks in these models was achieved by imposing long-run restrictions on the transitory component. Namely, the innovations to transitory components are restricted not to have any long-run impact on variables. In our analysis, however, a VAR consisting of permanent and transitory components has this property by construction.

From the definition of permanent and transitory components and from VECM we can establish a traditional autoregressive (AR) representation for $y_t = (\Delta P_t, T_t)$:

$$B(L)\, y_t = u_t \tag{21}$$

where u_t is the vector of permanent, u_{P_t}, and transitory innovations, u_{T_t}. The MA representation of y_t can be obtained by inverting the above model:

$$y_t = E(L)\, u_t. \tag{22}$$

Note that the second condition to identify the common factors insures that the total multiplier of T_t with respect to ΔP_t is zero, or $E_{12}(1) = 0$. Therefore innovations of the transitory component do not have a long-run impact on the levels of the permanent component. Hence we can easily implement the usual impulse response analysis to the system of permanent and transitory components to measure the impact of both permanent and temporary shocks.[10]

Figures 4 and 5 present impulse response functions for sectoral and aggregate output to structural shocks.[11] Temporary shocks have similar effects on sectoral outputs. They are usually hump-shaped, reaching their peak within a year. The effects of temporary shocks then decline to vanish after around eight years for all sectors. The exceptions to this type response are the resource-based sectors, Agr, Min and Egs. Responses of these sectors start declining immediately after the shock.

The effects of permanent shocks to sectoral outputs are mostly S-shaped. Within first eight quarters the responses reach a bottom from where they recover and cumulate. They reach highest level around four years and then stabilize over the initial impact level.

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[10] This is an easy way to analyze responses of the permanent and transitory components to different type of shocks but not the only one. Formally, the identification of permanent and temporary innovations can be achieved using Equations (2) - (5). There would be r temporary and m=p-r permanent innovations. However, in large systems, like ours, this type of analysis would generate p different responses of each component of a sector. To reduce the number of graphs and confusion we choose the analysis explained in the text. This way a sector is assumed to be subject to a mixture of certain type of shocks at any point in time.

[11] Blanchard and Quah (1989) denote structural disturbances to transitory components as 'demand shocks', and to permanent components as 'supply shocks'. Although these definitions are consistent with some theoretical work, empirically they are not identifiable as such. Therefore, we prefer to use 'temporary' and 'permanent' shocks instead.

Once again the resource-based sectors exhibit somewhat different behavior to a permanent shock. They show highly volatile responses before the effects stabilize.

Aggregate output exhibits responses similar to sectoral outputs for both temporary shocks and permanent shocks. The effect of a temporary disturbance is hump-shaped and reaches its peak within a quarter from where it declines sharply and dies out within eight years. Permanent disturbances have an effect on the level of aggregate output which shows a small spike within four quarters, after a short decline it cumulates steadily over time. The peak response is about eight times the initial effect and takes place after three years. Then it declines and stabilizes eventually.

It is apparent from these graphs that the 'temporary shocks' are not negligible in the short-run, defined as around eight years. This is the same conclusion reached by Blanchard and Quah (1989). On the other hand, the response of sectoral outputs to permanent shocks are substantially persistence and S-shaped which implicates productivity diffusion stories where it is claimed that the technological change is absorbed within a sector or economy rather slowly due to learning-by-doing effects or by different speeds of adoption at the firm level.

Potential Income and Permanent Component of Aggregate Output

Before closing the descriptive analysis of sectoral outputs and our aggregate measure, we compare our estimated permanent component of GDP to potential per capita income estimated by Denison (1985), for if the permanent component of aggregate output represents anything it is potential income. Denison's measure of potential income is computed by adjusting actual output using an Okun's-law relationship, by adjusting for capacity utilization, and by making other adjustments such as for labor disputes, the weather etc. In Figure 6 our estimated permanent component of GDP is plotted along with Denison's estimate. Although both estimates of long-run component of GDP are broadly similar, there are two major differences. The 1958 contraction and slowdown of 1970s.

IV. Analysis of Common Factors

In this section we attempt to associate each common factor to a variable or a certain group of variables. Ideally, if we find a long-run comovement between each of the common factors and a variable or set of variables, and if this variable or set of variables causes any of the common factors in the long-run, then we would be able to identify the sources of long-run growth for the economy.[12] For that matter we have chosen a small sample of possible variables and performed the necessary tests.

But before discussing possible associations of common factors to other possible variables, we examine the composition of these factors. As discussed in Section II, the estimated common factors are linear combinations of the variables in the system, that is, in our case, linear combinations of sectoral outputs. Therefore, we can test the importance of sectors in the long-run for the economy. Using Equations (15)-(18) we test whether certain sectors can be excluded from the linear combinations which form the common factors.[13] The test results, reported in Table 5, shows that three sectors' contribution, Dma, Ndm and Fin, to common factors are statistically significant. Although there is a controversy about the importance of manufacturing sector in the

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[12] While we were working on this project we became aware of the study by Ho and Sorensen (1993). Their approach is similar to ours, though the data and techniques used to identify the sources of driving forces for the economy are different from those employed in this paper.

[13] The common factor vectors are presented in Table 3. Since individual standard errors can not be calculated, we can only test whether a certain sector enters into all of the common factors or not, instead of assessing their relative importance.

recent literature, both durable and non-durable manufacturing have traditionally been viewed as the locomotive sectors of the economy. Especially, during the period under investigation there is no doubt that these sectors played an important role. Our finding that the third driving sector is financial services is probably a surprise to many. Actually, this result supports an old hypothesis, namely, the Schumpeterian argument that services provided by financial intermediaries are essential for economic growth since these services mobilize savings from inefficient uses to efficient ones, providing better monitoring of management and better evaluation of projects with different risks.

Now we proceed to investigate possible relationships between common factors and other variables. Since in neoclassical growth models the long-run movements in output arise from changes in productivity, first candidate for such causal involvement with common factors is naturally the productivity shocks. Due to lack of sufficient data points, we use here a graphical approach. In Figure 7 we graphed normalized versions of our estimated permanent innovations to non-durable manufacturing and Solow residuals calculated by Hall (1988).[14] The striking characteristic in this graph is that the series move closely except during the era of the sixties when the economy supported a war effort in Vietnam and the 1982 recession. This fact motivated us to investigate the details of the permanent innovations. One of the advantages of our multivariate analysis is that it enables us to identify more than one permanent innovations in the economy whose mixture constitute the trend. Regardless of whether these factors are different productivity shocks or other (possibly demand) factors, during certain sub-periods one factor may dominate the others so that the estimated mixture we call 'trend' may be misleading. In Figure 8 we plotted each of our three permanent innovations against Hall's

[14] Hall calculated Solow residuals for non-durable manufacturing. Therefore we use the permanent innovations to this sector for comparability. However, when we used permanent innovations to aggregate output we obtained very similar results.

productivity measure. In fact, the first permanent innovation moves closely with productivity during the sixties. The third shock captures the movement in productivity during 1982 while the second shock follows Hall's measure closely during seventies. From this graphical investigation we conclude that, if there are more than one and significantly different driving forces in the economy, as is likely, the Solow residuals are not capable of capturing their entire dynamics though they show strong similarities with some of these driving forces during certain sub-periods. Therefore aggregate models, or one-sector models, may very well be misleading as we claimed earlier.

Although the graphical comparison of the common factors with productivity was helpful, it is not sufficient for identifying the sources of the driving forces. Real business cycle models such as King, Plosser and Rebelo (1988) claim that the major source of growth is exogenous productivity shocks. In recent years this claim has been questioned in the literature. For example, Durlauf (1989) argues that the high degree of cointegration among sectoral outputs casts doubt on this interpretation of unit roots in real activity. Moreover, in a new study, Evans (1992) found that Solow residuals are not exogenous to certain variables. Finally, in King et al. (1991), the lack of explanatory power for a so-called "balanced growth" shock forced them to search for additional permanent components in the economy. To investigate these hypotheses we performed cointegration analyses between common factors and a few variables (X-factors) and tested whether they can be identified as sources of long-run growth. Ho and Sorensen (1993) use the proposition that if an exogenous X-factor lies in the unit root space spanned by the common factors then that factor X is a cause of long-run growth, to identify such sources. That is, if there are some exogenous variables which are cointegrated with the estimated common factors and if these variables cause the common factors in the long-run, then we can identify them as the sources of long-run growth.

Since there are not many aggregate variables for which exogeneity can be claimed a priori, we tested whether these factors are present in the linear combinations which form the new common factors.

The first set of variables we tried to associate with the common factors are a measure of money supply (M1), nominal interest rates (3-month Treasury Bill rates), and real government expenditures. We selected these variables because in real business cycle models the productivity shocks may be merely a reflection of omitted variables and these variables are omitted in many of such models. Moreover, these are the policy variables which shape the aggregate demand and possible associations of these variables with common factors may shed light on the claims of multiple equilibria or nominal rigidity theories. The results are presented in Tables 6-8. All three of the variables we examine here are cointegrated with the common factors. An interesting question is whether these variables are related to certain factors but not others. After successive testing we concluded that interest rates are moving with the first common factor while the money supply is cointegrated both with the first and second factors. When we performed similar analysis for real government expenditures, we find that a long-run equilibrium relationship exists between this variable and the third factor at 10% significance level. Our investigation suggests that monetary and fiscal policies in the US during the post-war era have different effects on the economy in the long-run. A more important question, however, is whether these variables are exogenous to the common factors, that is whether they are driving the economy in the long-run. We formed restrictions on common factors to test this hypothesis. The test results show that neither the policy variables nor the common factors are totally exogenous. Consequently, we conclude that, if the common factors we have estimated are productivity shocks, then our analysis suggests that these shocks are significantly affected by policy changes. But, it is also true that government policies are not exogenous themselves, they are also affected by or respond to unexplained changes in the economy.

The second set of variables we investigated are the inflation rate and the price of oil. It is a stylized fact that the inflation rate and productivity are negatively correlated. However, it is not clear whether there exists a causal relationship between the two and if so, which way the causality runs. Proponents of the no causality argument claim that the observed negative correlation comes from the supply shocks. An adverse supply shock would be expected to cause the growth of productivity to fall and inflation to rise. Since the most commonly cited specific example of a supply shock is the price of oil, we performed similar analysis for this variable as well. Although there is no positive proof that the estimated common factors are representing the productivity shocks, nevertheless, we tested whether they are cointegrated with inflation rate and oil prices. We find that inflation rate is cointegrated with the second common factor at 10% significance level and long-run causality runs in both directions. Again if one interprets the common factors as productivity residuals, we reject the hypothesis of no causality. Surprisingly, when we checked whether any long-run relationship exists between oil prices and common factors, we failed to detect any such relationship.[15] Yet it is still possible that changes in oil prices may influence common factors in the short-run.

V. Conclusion

The first goal of this paper was to decompose sectoral outputs into permanent and transitory components and assess the relative importance of the innovations to both of these components. We started by analyzing the degree of long-run comovement in

[15] Evans (1992) concluded similarly that oil price changes are misleading to identify productivity shocks.

sectoral outputs. During the post-war era in the US economy we found a substantial amount of cointegration across sectors which implies that the number of common trends in the data is much smaller than the number of sectors. This result casts doubt on the underlying assumption used by Long and Plosser (1983) to explain the variation in outputs in which each sector is assumed to be subject to idiosyncratic shocks. Further our permanent-transitory decomposition of aggregate and sectoral outputs revealed that the business cycles may not be alike across sectors. While the permanent and transitory components are negatively correlated throughout the entire sample, during some NBER recessions the downturn of the economy are partially due to the decline in permanent components in contradiction to univariate analyses where the recessions are solely due to temporary components.

To understand the importance of the innovations to permanent and transitory components we performed impulse response analyses. The effects of temporary shocks were usually hump-shaped and last for a considerable amount of time while the effects of permanent shocks showed undoubtedly high persistence. The S-shaped responses of outputs to permanent innovations are interpreted as being consistent with technological diffusion, a characteristic which is missing in many of other decomposition analyses.

The second goal of this paper was to answer the question which is raised by the finding of a high degree of long-run comovement among sectoral outputs and concerns the sources of the innovations. In the literature, two different interpretations for this phenomenon are provided. Issler and Engle (1992) suggest that the observed comovement may be due to the fact that the dimension of technology shocks is smaller than the dimension of the sectors, that is, productivity shocks are cointegrated among themselves. Durlauf (1989), on the other hand, points out the possibility of other factors which link sectoral outputs in the long-run. To investigate this question we performed a common factor analysis and identified the driving forces in the economy as observable. First we tested whether certain sectors can be identified as the ones which are driving the economy in the long-run and concluded that durable and non-durable manufacturing and financial services can be singled out as the locomotive sectors of the economy. We claimed that our finding that the financial services are an important sector in the long-run can be viewed as support for the Schumpeterian argument that financial intermediation can accelerate growth.

We also analyzed possible relationships between the estimated common factors and other macroeconomic variables. The graphical analysis of common factors and Solow residuals showed that none of the common factors mimic Solow residuals closely throughout the sample, but each of them shows some significant similarity during certain sub-periods. Consequently we examined whether certain policy variables are contributing to the movement in common factors. We found that both monetary and fiscal policy instruments have important effects on the economy in the long-run. Yet we also concluded that these policies are not completely exogenous to the changes in the economy. As a whole, our results cast doubt about the real business cycle models which assume strictly exogenous productivity shocks and completely disregard the importance of demand shocks.

Throughout this paper we investigated the movements in sectoral outputs in the US economy to study the properties of aggregate fluctuations. Our findings call for new theoretical models where both productivity and demand shocks play equally important roles and models which can explain the different behavior of trend components during different recessions. It would be interesting to repeat the same analysis for other countries to test the robustness of our findings internationally. Also, the comovement of sectoral outputs across countries can provide insight for understanding the nature of global shocks which we totally ignored here.

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APPENDIX A: The Data

The data consist of seasonally adjusted quarterly observations for the US economy and mainly available from Citibase with the exception of sectoral price deflators. While our analysis covers a period of forty years which, for all practical purposes, can be considered a long span, it is a familiar fact to the empirical researchers that small number of observations introduces bias to the estimation, especially when our kind of analysis is performed. Therefore, instead of using annual data we chose to interpolate annual sectoral deflators to obtain real output series. For that matter, we used Chow and Lin's (1971) interpolation technique. Further, to obtain more precise estimates we interpolated the inflation rates rather than the price deflators themselves. The idea of Chow-Lin technique in its simplest form is that to each annual series to be interpolated, Y_{it}, is associated a number of quarterly series, x_{it}, that a priori information suggests move within the year the way quarterly observations on the annual dependent variable would. (Annual variables are denoted with capital letters, whereas for the quarterly variables lower case latters are used). The quarterly explanatory variables are annualized, X_{it}, and a regression is run over the generated annual data:

$$Y_{it} = X_{it}\beta + U_t \tag{A1}$$

Moreover, we assumed that the quarterly errors follow an AR(1) process. This induces a complication on the covariance structure of the annual error term. The autocorrelation term of U_t, ρ_A , is related to the quarterly autocorrelation coefficient, ρ_Q , by the non-linear formula:

$$\rho_A = \frac{\rho_Q^7 + 2\rho_Q^6 + 3\rho_Q^5 + 4\rho_Q^4 + 3\rho_Q^3 + 2\rho_Q^2 + \rho_Q}{2\rho_Q^3 + 4\rho_Q^2 + 6\rho_Q + 4} \tag{A2}$$

By running (A1) and solving (A2) for ρ_Q we obtained estimates for both β and ρ_Q. These estimates are then used to generate quarterly observations for the dependent variable as:

$$\hat{y}_{it} = x_{it}\hat{\beta} + \hat{\rho}_Q\hat{u}_{t-1} \tag{A3}$$

In our case, the dependent variables, y_{it}, are the quarterly sectoral inflation rates. As x_{it} we used a constant term a time trend and log differences of quarterly GDP deflators.

The quarterly nominal sectoral outputs and other variables used in this paper are taken form Citibase (their Citibase mneumanics are given in brackets): Agriculture, Forestry and Fishing, [GYAFF], Mining [GYWM], Construction [GYWC], Durable Manufacturing, [GYMD], Non-durable Manufacturing [GYMN], Transportation and Communication [GYT + GYC], Electric, Gas and Sanitary Services (Utilities) [GYUT], Domestic Trade [GYNRW + GYNRR], Finance, Insurance, and Real Estate Services [GYFIR], Other Services [GYS]. The sectoral outputs are then divided by generated sectoral price deflators and total civilian non-institutional population [P16] to obtain real per capita outputs. Other variables used in the paper are money supply [FM1], interest rates [FYGM3], real (federal) government expenditures [GGEQ] and inflation rate measured as log differences of quarterly GDP deflator [GD].

APPENDIX B: Model Specification

In empirical research it is important to build a model which takes the properties of the data into account as well as answers the needs of the theory. The problem of model building gets more difficult when economic theory does not provide researcher a certain structure. Throughout this paper we assumed that there exists a True Data Generating Process which has to be approximated by the Statistical Model. We encountered mainly with two problems when specifying the dynamics of the model. First, the asymptotic distribution of the trace statistics depends on the deterministic part of the Data Generating Process. Second, we observed a pattern in the data that the number of cointegrating relationships increase with the lag length, although there is no theoretical reason for that. We pursued the following strategy which is also known as general-to-specific methodology.

The asymptotic distribution of the test statistics to determine the cointegration rank depends on the choice of deterministic variables. The two most commonly used models are distinguished from each other by the restrictions imposed on the coefficients of the non-stochastic part of the Data Generating Process. The general model contains a linear deterministic trend in error correction representation which gives rise to a quadratic trend in the moving average representation (Equation (2) in the paper). The second model allows only linear trends in the levels.

(M1) $\Delta X_t = \Gamma_1 \Delta X_{t-1} + \dots + \Gamma_{k-1} \Delta X_{t-k+1} + \Pi X_{t-k} + \mu_0 + \mu_1 t + \varepsilon_t$

(M2) $\Delta X_t = \Gamma_1 \Delta X_{t-1} + \dots + \Gamma_{k-1} \Delta X_{t-k+1} + \Pi X_{t-k} + \mu_0 + \varepsilon_t$

The significance of restrictions can be tested by using Likelihood Ratio tests which have standard χ^2 distribution with h degrees of freedom where h is the number of restrictions.

To determine which Statistical Model is appropriate for the VECM of sectoral outputs, tests on the deterministic variables have been performed for every lag structure, starting from the most general model. The chosen models are reported and used in the paper.

The choice of lag length is important for too few lags may cause inconsistency while too many lags may lead to inefficiency in estimation. To determine the lag length we estimated Akaike(AIC) and Schwarz Information Criteria (BIC). The BIC indicated only one lag which seems to be very few. The AIC suggested eight lags of levels when we analyzed the comovement of sectoral outputs. In previous literature where annual data is used it is claimed that the dynamics can be captured with a VECM of order two. Therefore, we concluded that the choice of eight lags is adequate for quarterly data.

Table 1: Augmented Dickey-Fuller Unit Root Tests

$$\Delta y_t = c_0 + c_1 t + \sum_{i=1}^{4} a_i \Delta y_{t-i} + \varepsilon_t$$

	Lags=1	Lags=2	Lags=3	Lags=4	Lags=5	Lags=6	Lags=7	Lags=8
Agr	-4.027	-2.617	-2.036	-2.15	-1.907	-1.569	-1.154	-1.047
Min	-1.924	-2.104	-1.862	-1.865	-1.723	-1.881	-2.139	-2.162
Con	-2.316	-2.392	-2.337	-2.400	-2.966	-2.765	-2.413	-2.521
Dma	-3.236	-3.155	-3.737	-2.907	-2.922	-2.872	-2.786	-2.357
Ndm	-1.883	-1.721	-1.485	-1.165	-1.047	-1.042	-.948	-0.768
Tco	-3.690	-3.716	-4.070	-3.845	-3.884	-3.640	-3.314	-2.684
Egs	-2.908	-2.440	-2.137	-2.096	-2.044	-2.104	-2.006	-2.049
Trd	-1.839	-2.344	-2.381	-2.265	-2.392	-2.228	-2.265	-2.375
Fin	-1.762	-1.368	-1.631	-1.584	-1.692	-2.029	-2.751	-2.485
Ser	-2.609	-2.959	-3.175	-3.228	-3.162	-3.117	-2.844	-3.187
GDP	-3.273	-3.347	-3.735	-3.311	-2.986	-3.183	-3.210	-2.484

The 1%, 5% and 10% critical values for the ADF test statistics are -4.02, -3.44, and -3.14, respectively. These values are obtained using the simulated response surfaces given in MacKinnon (1990).

Table 2: Cointegration Analysis

Null Hypothesis	Trace Statistic	Critical Value (at 95%)
∃ at most 0 cointegrating vector	459.57	250.84
∃ at most 1 cointegrating vectors	350.46	208.97
∃ at most 2 cointegrating vectors	270.80	170.80
∃ at most 3 cointegrating vectors	193.55	136.61
∃ at most 4 cointegrating vectors	125.57	104.94
∃ at most 5 cointegrating vectors	89.57	77.74
∃ at most 6 cointegrating vectors	58.07	54.64
∃ at most 7 cointegrating vectors	30.61	34.55
∃ at most 8 cointegrating vectors	12.33	18.17
∃ at most 9 cointegrating vectors	0.71	3.74

Eigenvalues

0.5122 0.4079 0.3984 0.3606 0.2109 0.1872 0.1653 0.1133 0.0736 0.0047

Table 3: Estimates of Factor Model

Cointegrating Matrix β

	z1	z2	z3	z4	z5	z6	z7
Agr	0.6571	22.9614	-25.8352	-1.2766	2.3671	-6.4727	-12.7860
Min	-11.6367	11.3194	14.9122	-13.2399	-12.7284	1.4108	11.7425
Con	38.2869	17.8765	-10.2794	-8.3365	38.2225	49.1684	-6.3930
Dma	-82.3042	-27.2774	-11.7703	59.4936	-25.9462	-25.1486	35.3168
Ndm	76.4093	67.1050	-44.7371	-30.5618	-10.1783	19.0661	-37.0714
Tco	122.2521	-20.0902	11.7928	20.7091	115.4958	42.2433	-48.9508
Egs	19.7489	40.6484	15.5992	-61.7095	-30.6394	25.9108	-1.7283
Trd	6.3359	9.2570	33.9750	-19.6315	-35.9072	15.6742	-34.3203
Fin	-79.4313	-0.2447	39.2042	86.7581	-70.3955	-11.1421	22.7177
Ser	47.6223	-15.5144	48.7071	-133.4214	53.2164	-128.9409	-45.2209

Common Factor Matrix $\hat{\alpha}_{\perp}$

	f1	f2	f3
Agr	0.4907	4.5859	11.2330
Min	14.1651	6.3059	12.0214
Con	1.5563	-37.6913	-25.2661
Dma	4.6045	28.5531	-25.3001
Ndm	-43.5689	-12.6886	-14.7211
Tco	62.5414	-47.5678	16.6181
Egs	2.0315	-27.1868	-11.2522
Trd	-14.9721	39.7666	-2.8564
Fin	-51.5063	-8.5688	55.1051
Ser	-6.9148	99.6370	15.6578

Factor Loading Matrix A1

0.0090	0.0059	-0.0132	0.0109	-0.0017	0.0090	0.0127	0.0004	-0.0042	-0.0019
-0.0094	0.0334	0.0041	-0.0024	0.0074	-0.0042	-0.0238	0.0082	-0.0056	-0.0007
0.0062	0.0130	-0.0060	-0.0223	-0.0047	-0.0054	-0.0154	-0.0016	-0.0007	-0.0038

Factor Loading Matrix A2

-0.0278	0.0179	-0.0143	-0.0003	0.0162	0.0043	-0.0074	-0.0041	-0.0031	-0.0017
0.0122	0.0235	0.0154	0.0184	0.0091	0.0060	0.0074	-0.0014	0.0083	0.0058
-0.0089	0.0071	0.0099	0.0119	0.0013	0.0067	0.0095	0.0029	0.0090	0.0058
-0.0043	0.0068	-0.0010	0.0140	0.0088	0.0079	0.0000	0.0002	0.0051	0.0007
0.0096	0.0069	0.0240	0.0000	-0.0048	-0.0021	-0.0087	-0.0015	0.0036	0.0051
-0.0016	0.0130	0.0099	-0.0159	-0.0054	-0.0082	-0.0174	0.0094	-0.0056	-0.0060
-0.0344	0.0465	0.0022	-0.0044	0.0139	-0.0054	-0.0207	-0.0122	-0.0033	-0.0012

Table 4a: Sample Statistics for Sectoral Outputs and Their Components

	Series		Permanent Component (P)		Transitory Component (T)		Correlation between P & T
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	
Agriculture	5.9444	0.1499	5.9444	0.0808	–	0.1349	-0.0850
Mining	5.3101	0.2201	5.3101	0.1934	–	0.1364	-0.1322
Construction	7.1580	0.1357	7.1580	0.1223	–	0.0864	-0.1748
Dur. Manuf.	7.6744	0.1358	7.6744	0.0131	–	0.0627	-0.1916
Non-dur. Manuf.	7.2721	0.1812	7.2721	0.1706	–	0.0683	-0.0336
Tran.&Commun.	6.6788	0.2234	6.6788	0.2227	–	0.0344	-0.0445
EG&S	6.0031	0.1445	6.0031	0.1462	–	0.0647	-0.2678
Dom. Trade	7.7624	0.1917	7.7624	0.1893	–	0.0334	-0.0288
F.I.R.E. Services	7.7405	0.2310	7.7405	0.2311	–	0.0295	-0.1036
Other Services	7.9331	0.2702	7.9331	0.2697	–	0.0251	-0.0085
GDP	9.5444	0.1555	9.5444	0.1529	–	0.0271	-0.0322

Table 4b: Sample Statistics for Differenced Sectoral Outputs and Permanent Components

	Difference of Series		Diff. of Permanent Component		Correlation between
	Mean	Std Dev	Mean	Std Dev	ΔP & T
Agriculture	-0.0013	0.0610	-0.0010	0.0242	0.0098
Mining	-0.0016	0.0201	-0.0007	0.0654	-0.2882
Construction	0.0018	0.0350	-0.0028	0.0264	-0.2619
Dur. Manuf.	0.0032	0.0230	0.0024	0.0432	-0.3011
Non-dur. Manuf.	0.0047	0.0186	0.0039	0.0145	-0.1627
Tran.&Commun.	0.0014	0.0436	0.0051	0.0187	-0.2043
EG&S	0.0041	0.0140	0.0021	0.0542	-0.3085
Dom. Trade	0.0047	0.0135	0.0046	0.0137	-0.0169
F.I.R.E. Services	0.0061	0.0075	0.0048	0.0123	-0.1470
Other Services	0.0033	0.0129	0.0059	0.0082	-0.3034
GDP	-0.0049	0.0242	0.0034	0.0112	-0.2403

Table 5: Testing Restrictions on Common Factors

$$H_0 : \hat{\alpha}_\perp = G\,\phi$$

Excluded Sector(s)	p-value
Agriculture	0.0295
Mining	0.0437
Construction	0.1494
Durable Manuf.	0.0079
Non-durable Manuf.	0.0006
Transportation & Communication	0.0105
Electricity, Gas & Sanitary Services	0.0268
Domestic Trade	0.1437
F.I.R.E. Services	0.0082
Other Services	0.1384

Table 6: Cointegration Analysis of Common and X Factors*

Rank	X-Factor: Nominal Interest Rates	Money Supply	Government Expenditure	Inflation Rate	Oil Prices
0	51.97**	53.81	60.53	53.63	40.14
1	15.11	24.17	24.50	22.14	22.93
2	4.75	11.59	9.12	9.44	8.48
3	0.85	2.12	0.36	0.87	0.42

Table 7: Testing Restrictions on Cointegration Vectors***

Excluding	X-Factor: Nominal Interest Rates	Money Supply	Government Expenditure	Inflation Rate	Oil Prices
f_1	0.0010	0.0412	0.1252	0.3657	–
f_2	0.3652	0.0015	0.2863	0.0933	–
f_3	0.5189	0.8876	0.0624	0.7372	–
X	0.0000	0.0000	0.0000	0.0000	–
f1 and f2	–	–	0.2786	–	–
f2 and f3	0.6701	–	–	–	–

Table 8: Testing Restrictions on Common Factor Matrix***

Excluding	X-Factor: Nominal Interest Rates	Money Supply	Government Expenditure	Inflation Rate	Oil Prices
f_1	0.0048	0.0013	0.0000	0.0017	–
f_2	0.0000	0.0025	0.0009	0.0034	–
f_3	0.0000	0.0003	0.0000	0.0001	–
X	0.0001	0.0005	0.0051	0.0062	–

* The estimation is run from 1954:1-1991:4 except for Money Supply for which data was available only from 1959:1 to 1991:4. The model used is M1 as described in Appendix B. Only for interest rates model M3 could not be rejected. The lag length is eight in levels except for interest rates for which we used six lags.

** The critical values are taken from Osterwald-Lenum (1992) and as follows:

Rank	M1 90%	M1 95%	M3 90%	M3 95%
0	50.71	54.64	43.95	50.35
1	31.42	34.55	26.79	29.68
2	16.06	18.17	13.33	15.41
3	2.57	3.74	2.69	3.76

*** The p-values are reported.

Figure 1-a: Shares of "Goods" Sectors in Total Output

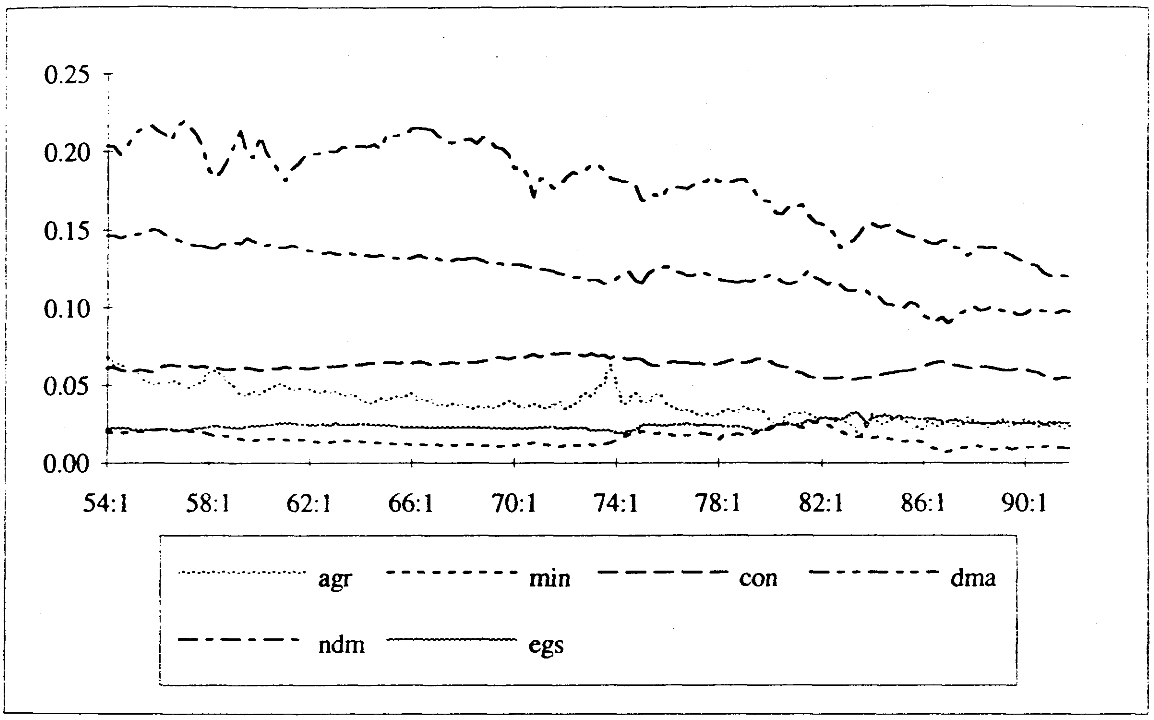


Figure 1-b: Shares of "Service" Sectors in Total Output

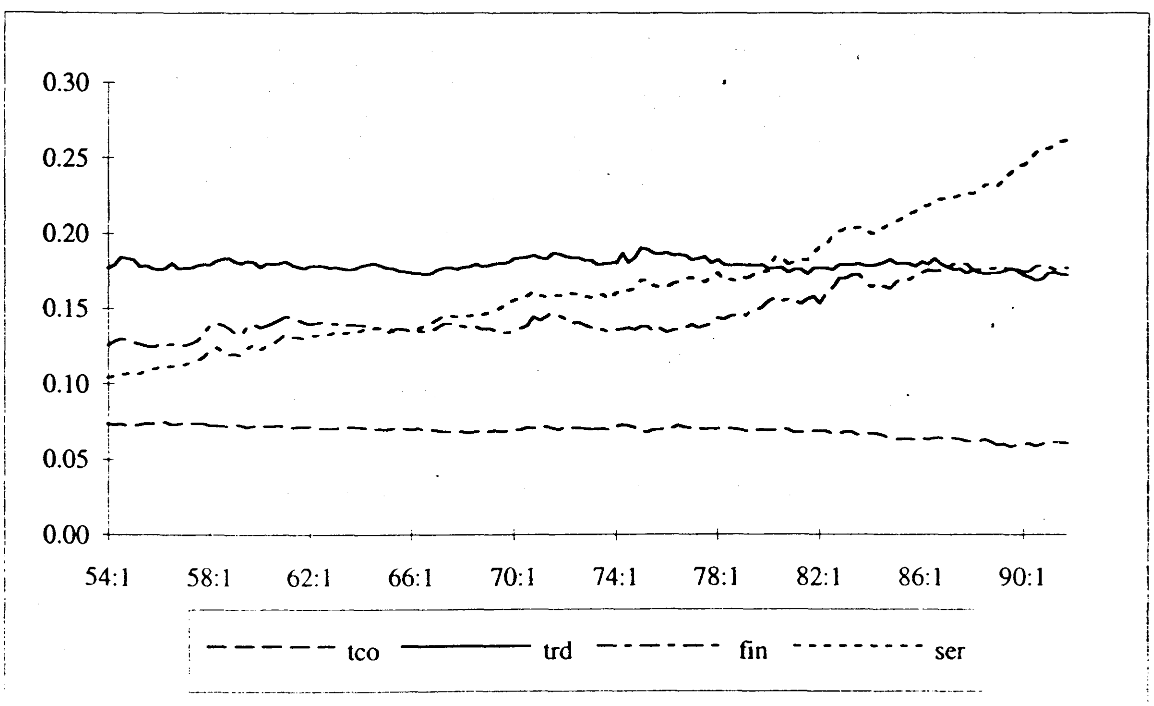


Figure 2-1a: Agriculture Output and its Permanent Component

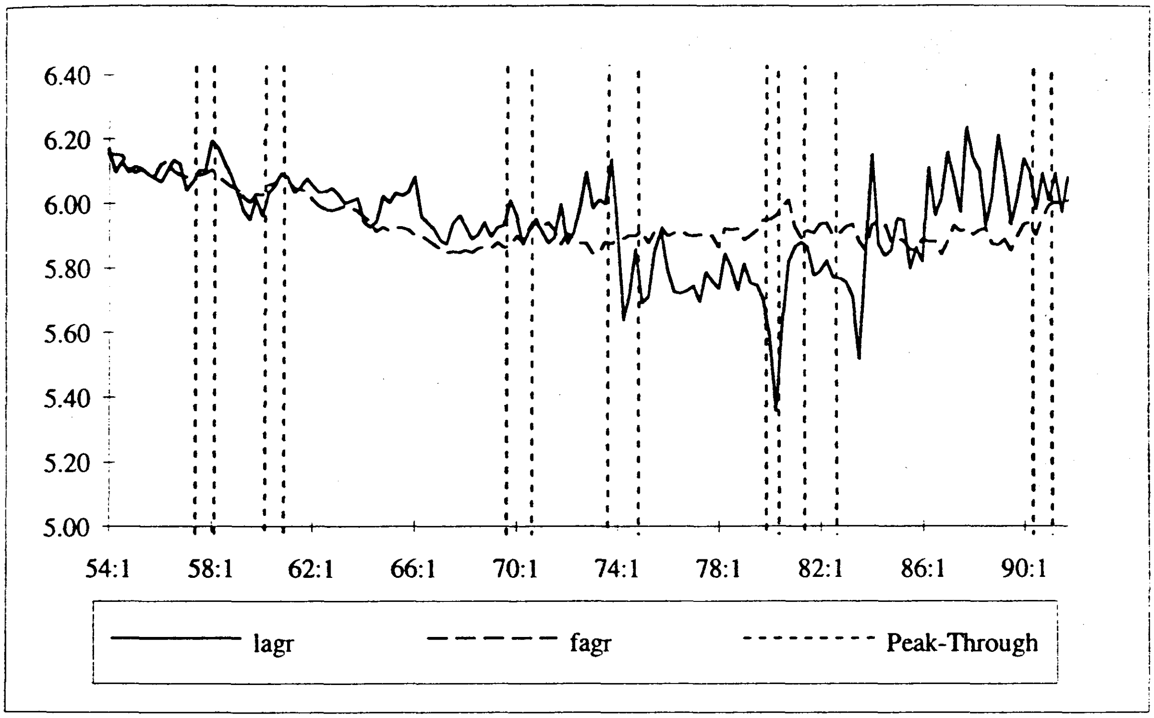


Figure 2-1b: Transitory Component of Agriculture

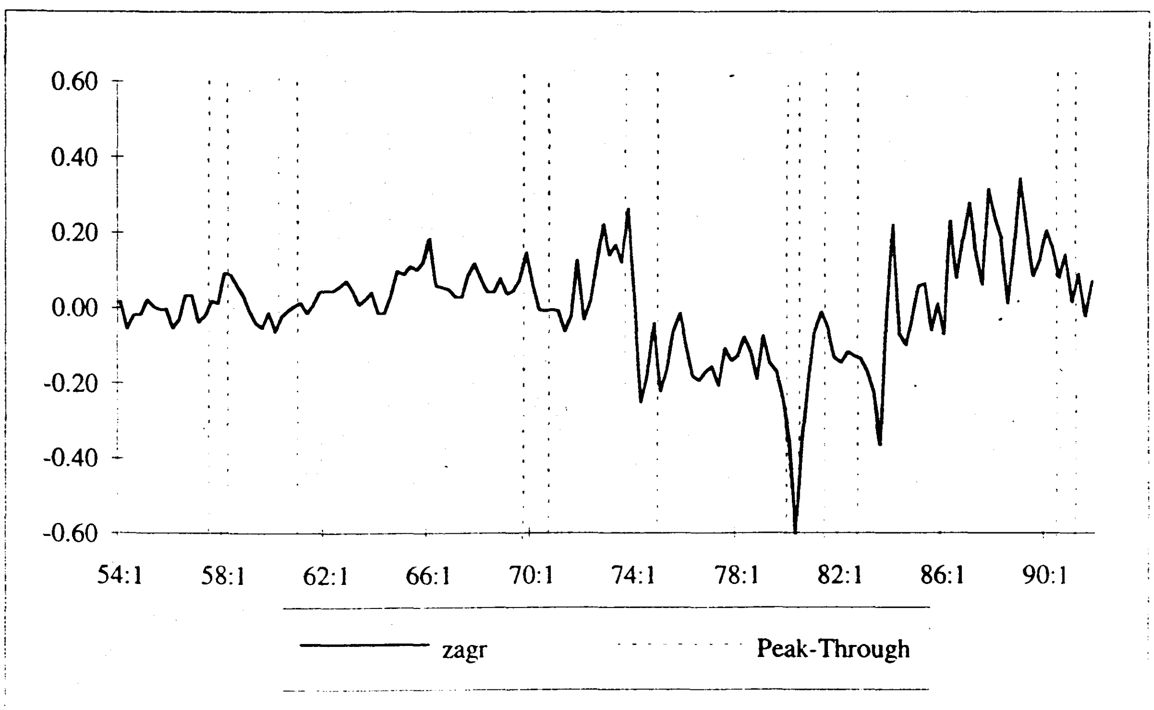


Figure 2-2a: Mining Output and its Permanent Component

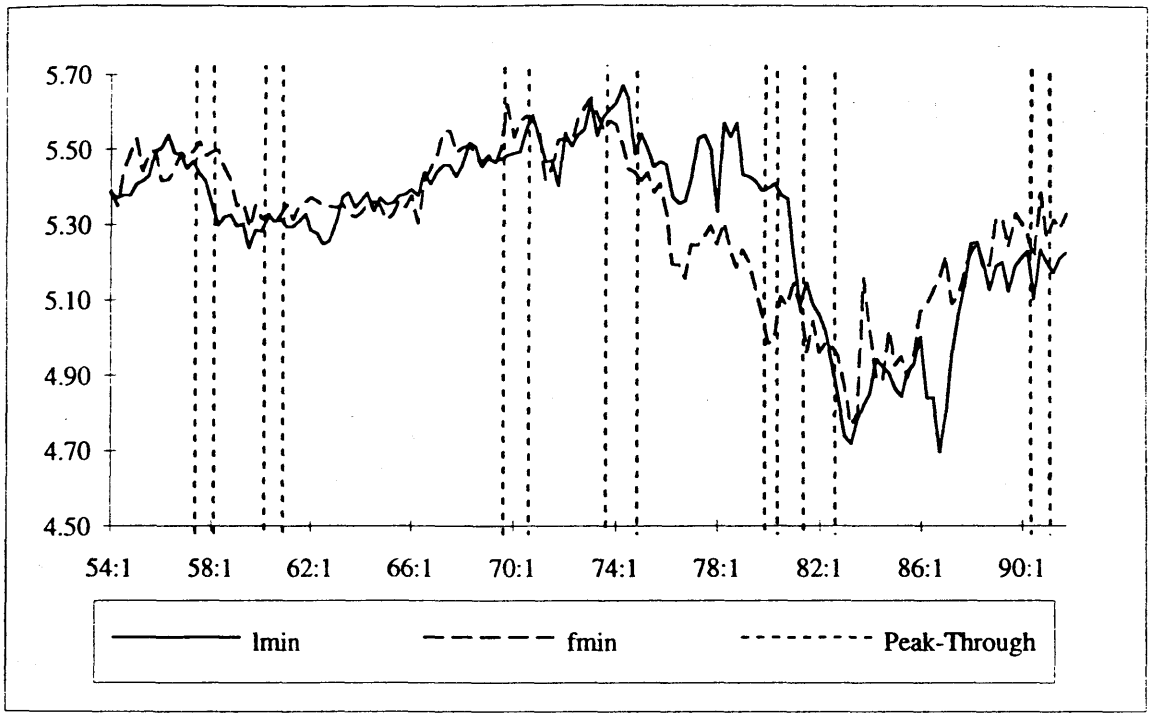


Figure 2-2b: Transitory Component of Mining

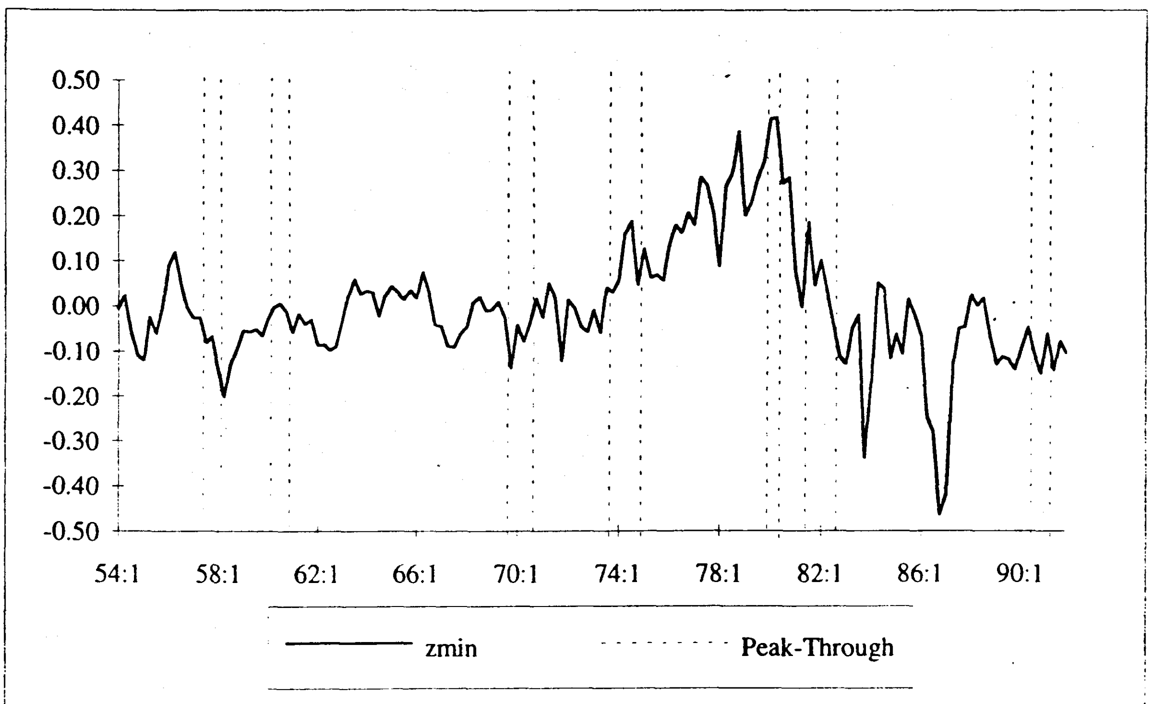


Figure 2-3a: Construction Output and its Permanent Component

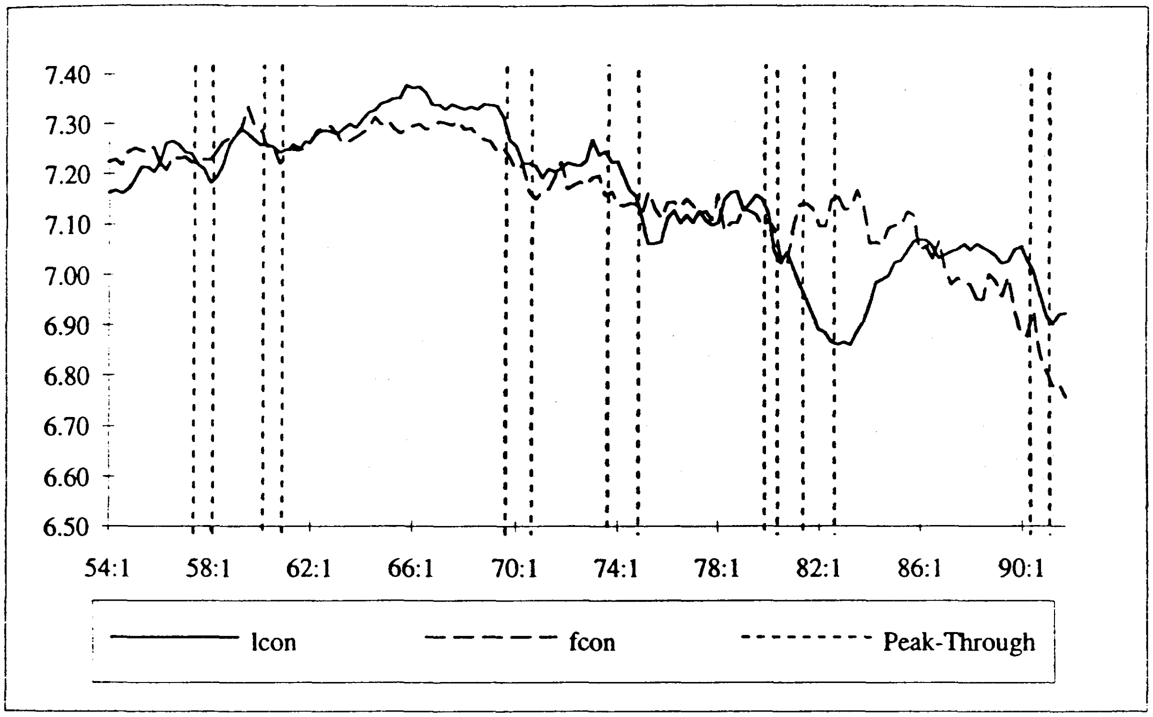


Figure 2-3b: Transitory Component of Construction

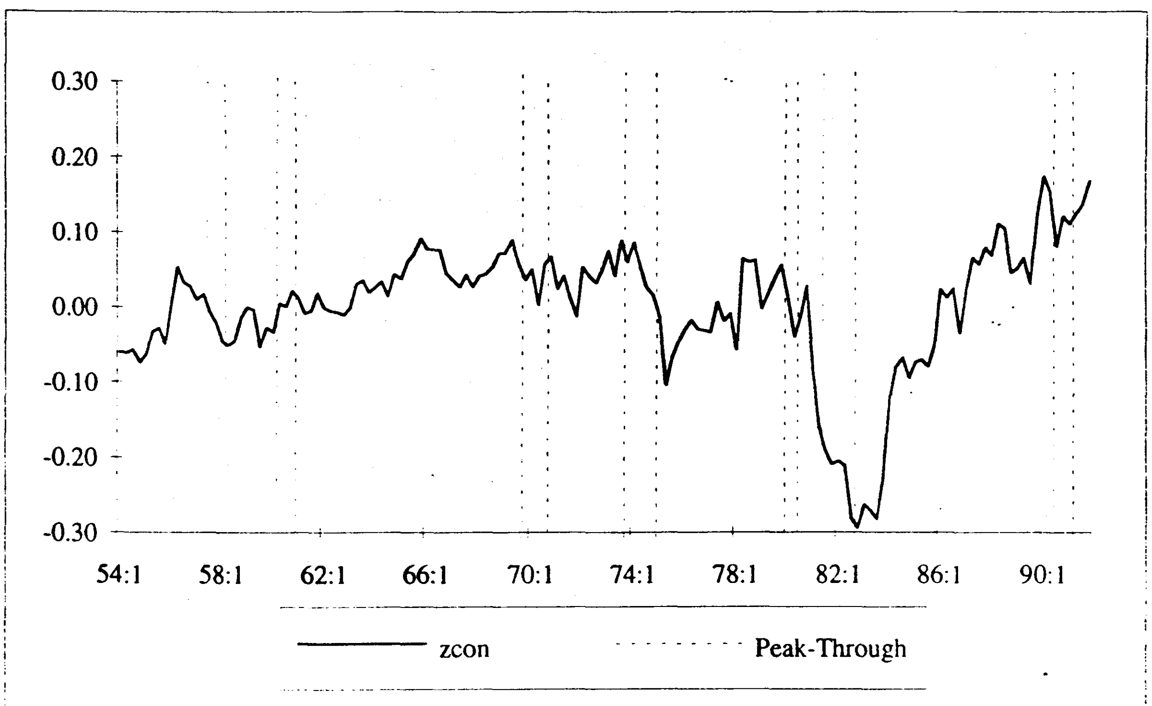


Figure 2-4a: Durable Manufacturing Output and its Permanent Component

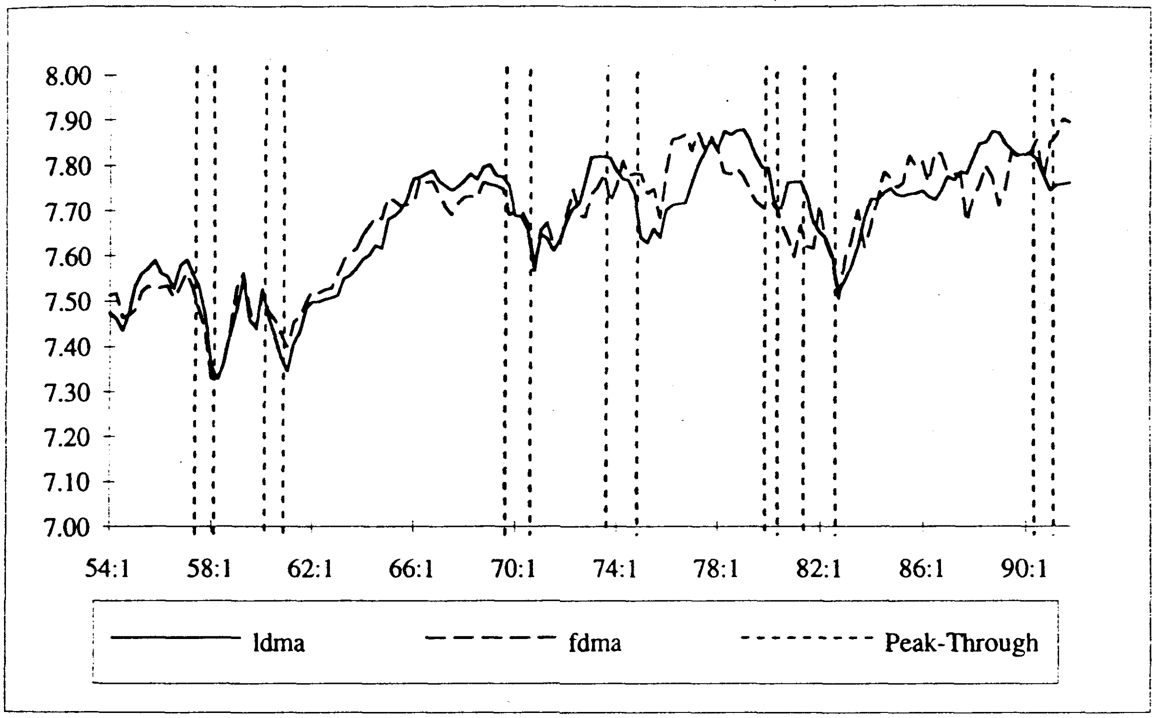


Figure 2-4b: Transitory Component of Durable Manufacturing

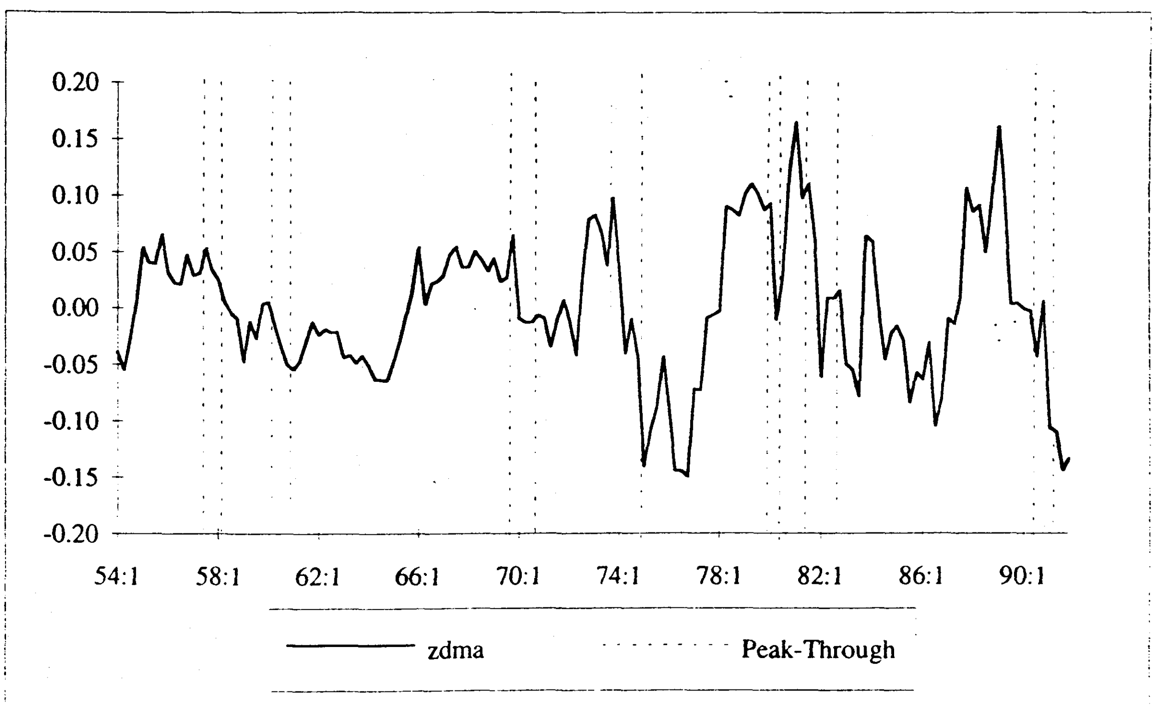


Figure 2-5a: Non-durable Manufacturing Output and its Permanent Component

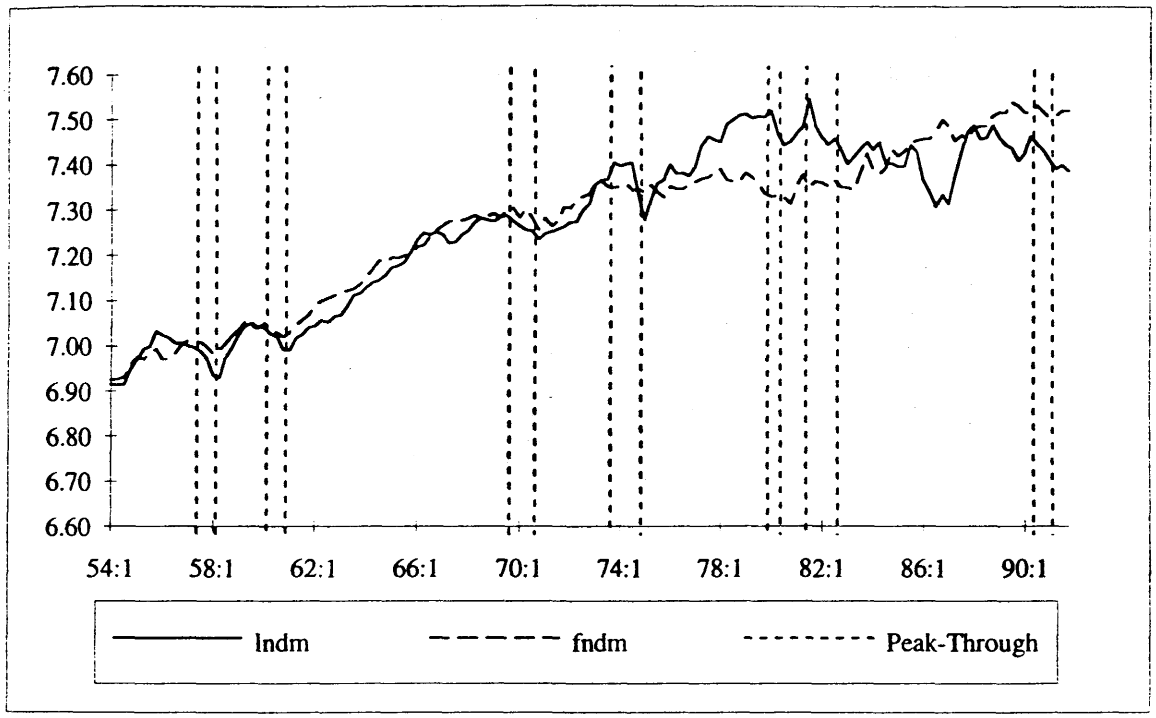


Figure 2-5b: Transitory Component of Non-durable Manufacturing

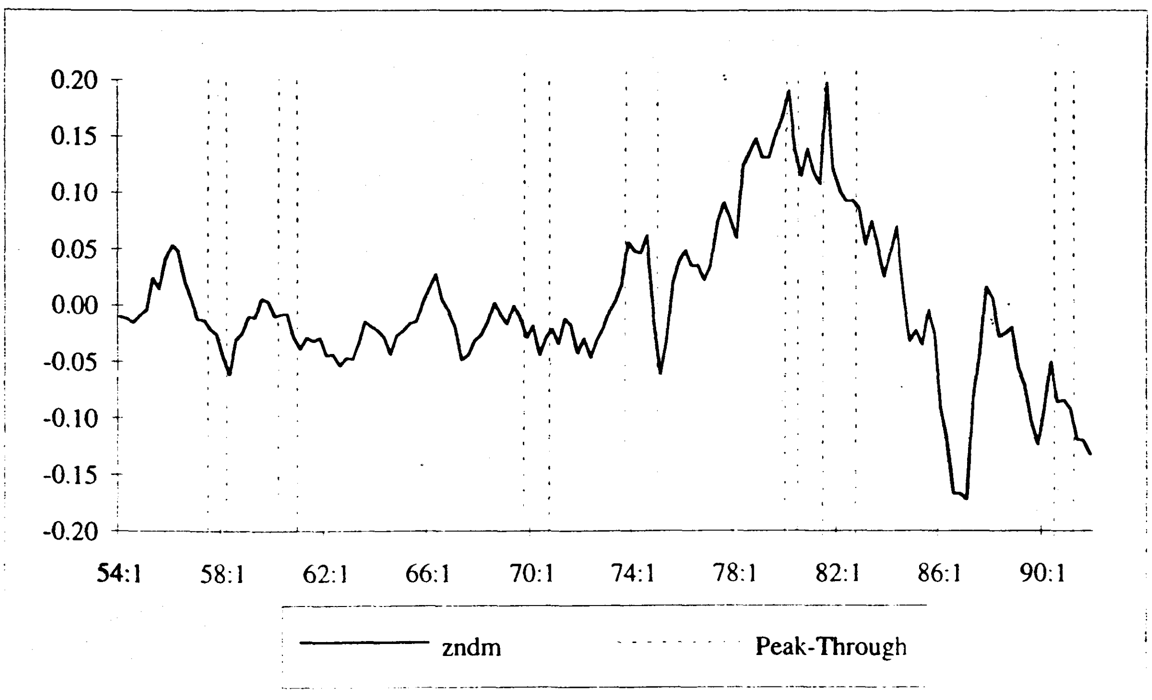


Figure 2-6a: Trans. & Communication Output and its Permanent Component

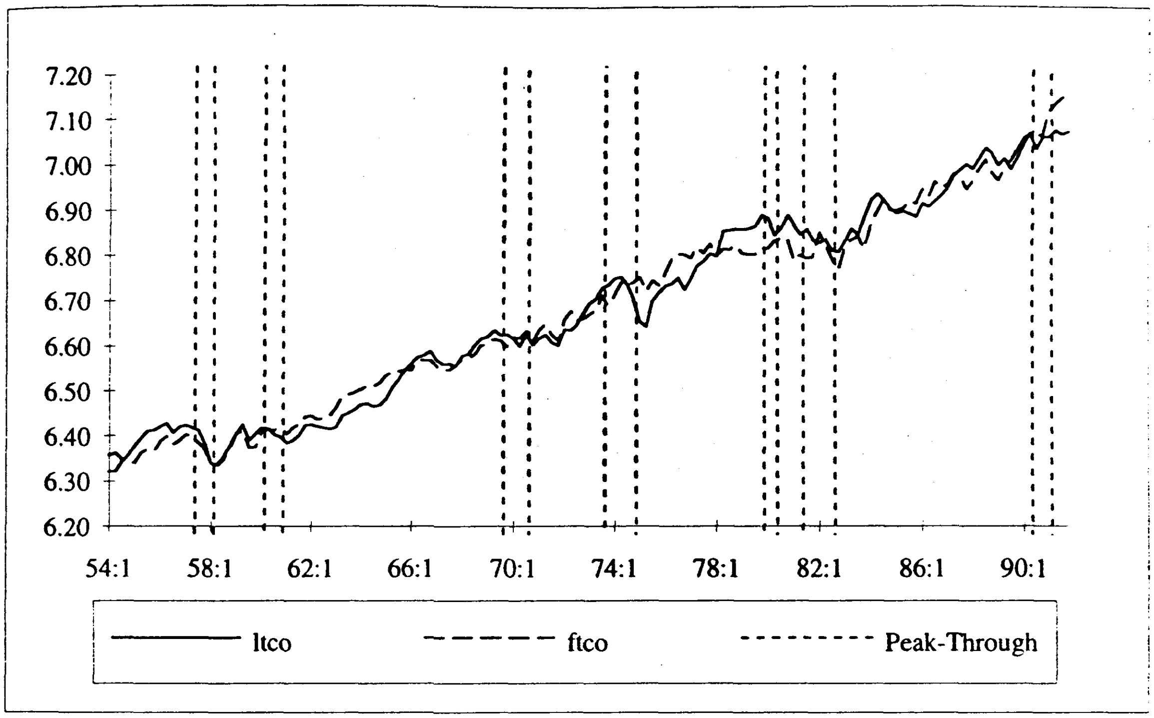


Figure 2-6b: Transitory Component of Trans. & Communication

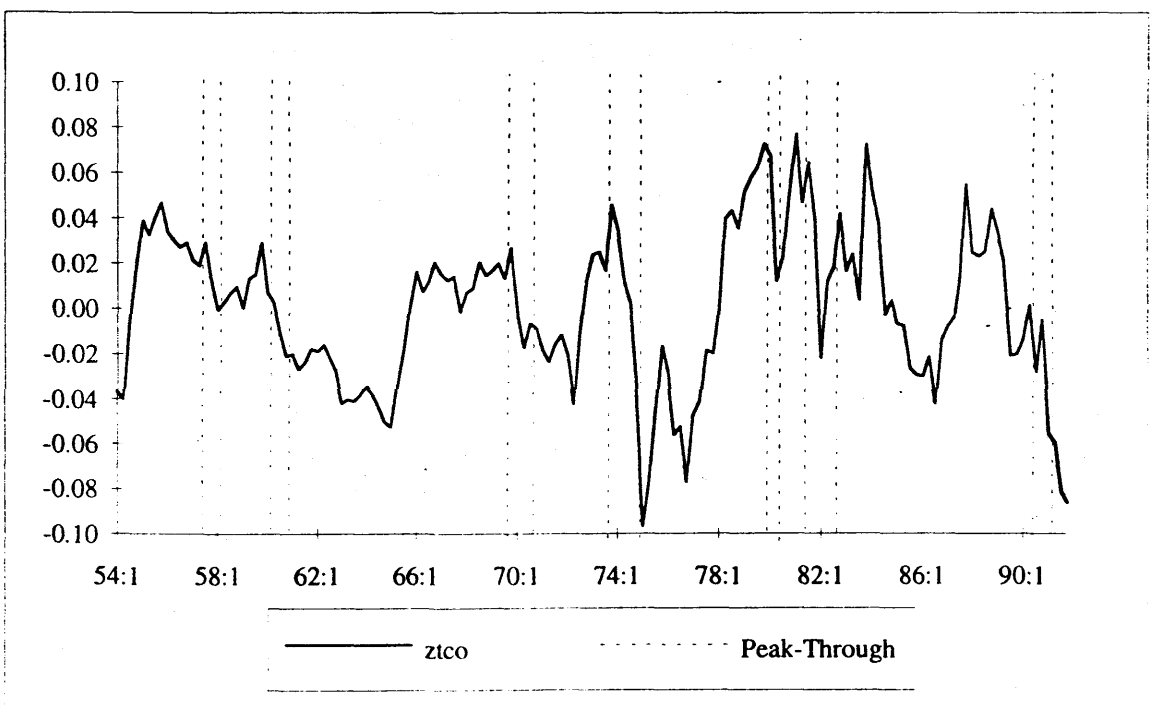


Figure 2-7a: EG&S Services Output and its Permanent Component

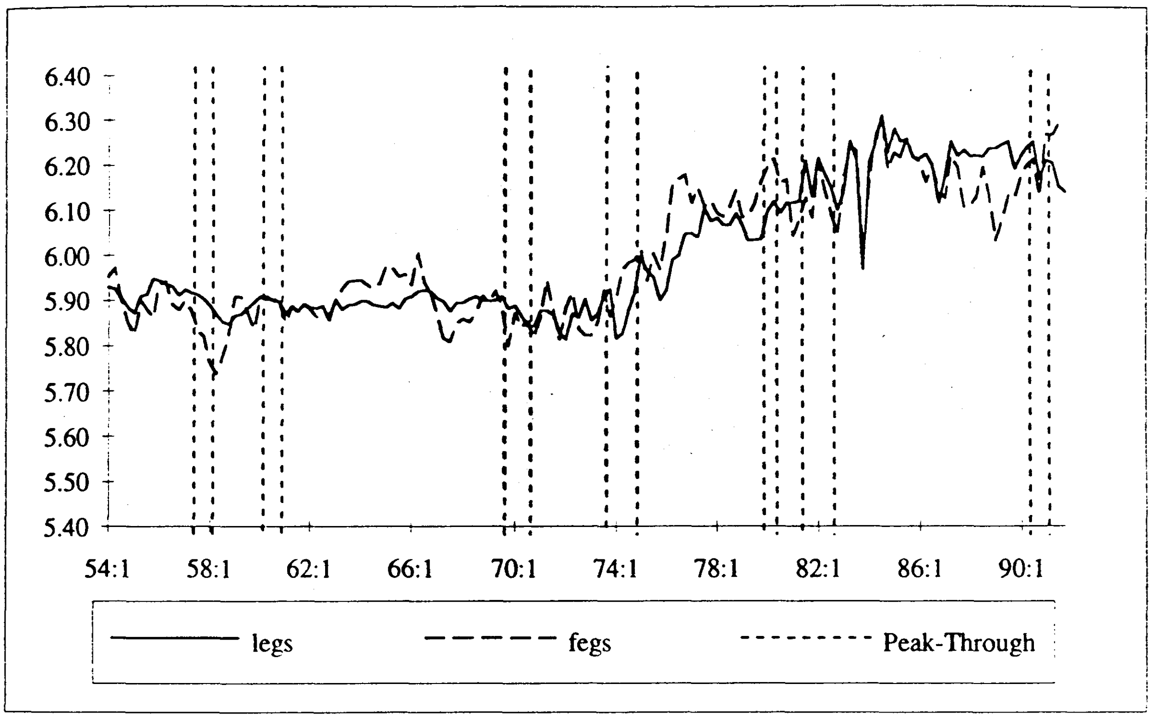


Figure 2-7b: Transitory Component of EG&S

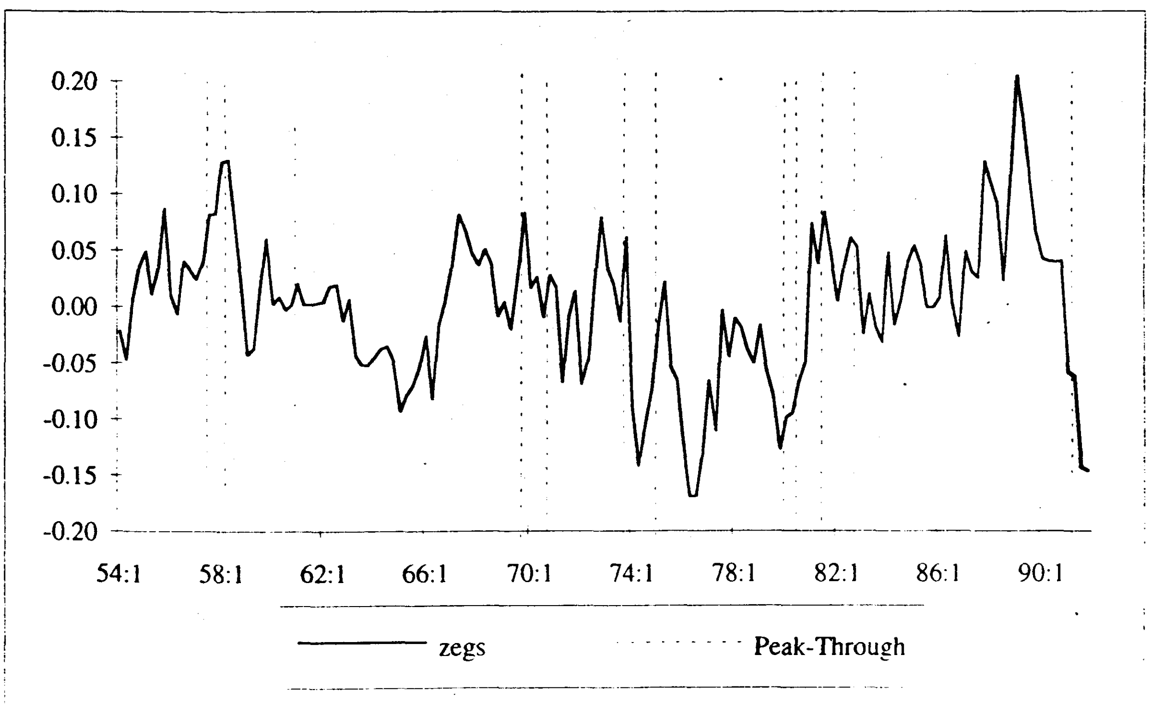


Figure 2-8a: Domestic Trade Output and its Permanent Component

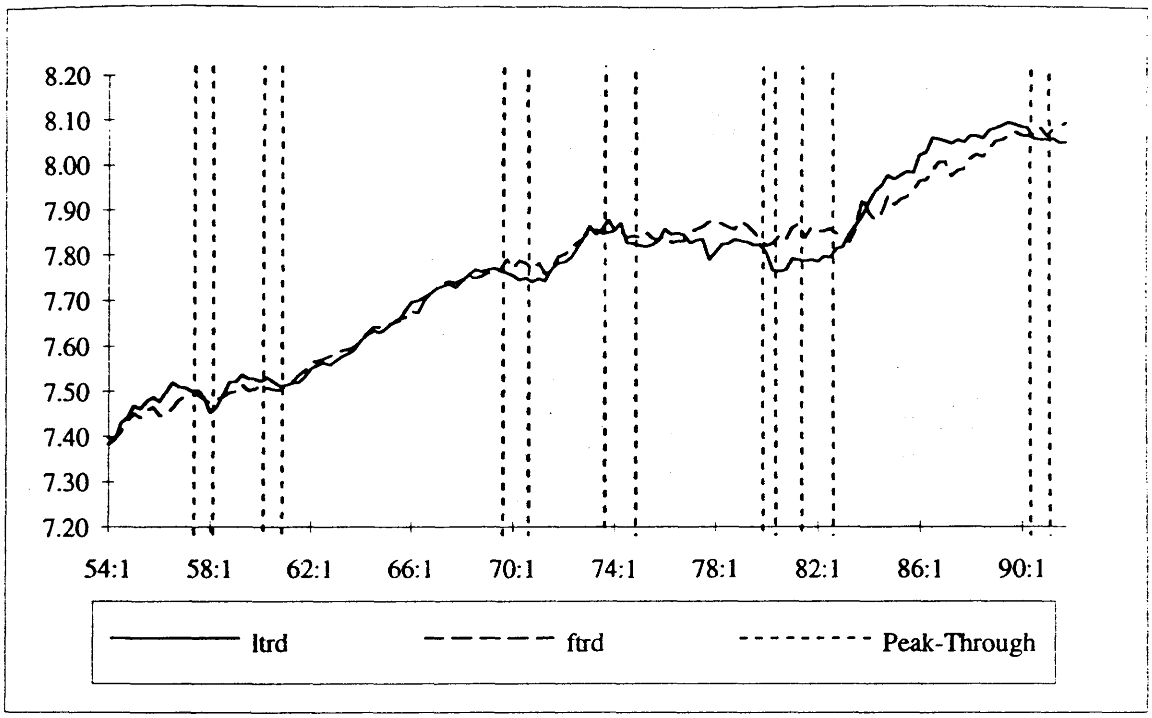


Figure 2-8b: Transitory Component of Domestic Trade

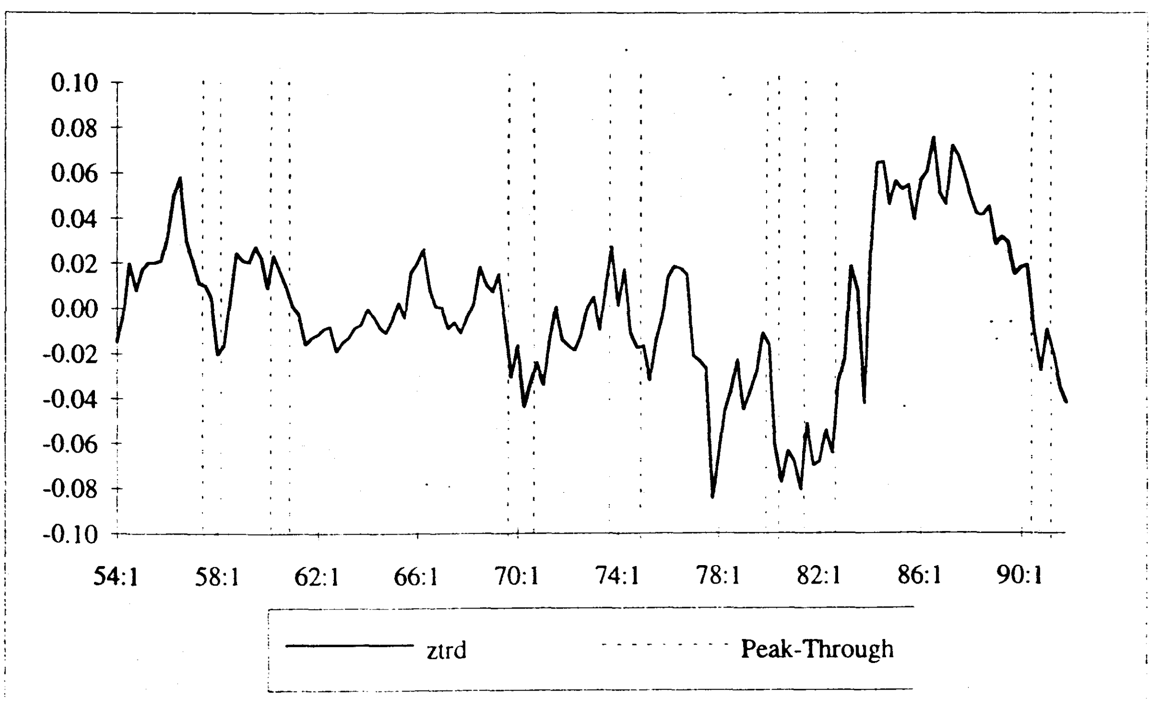


Figure 2-9a: F.I.R.E. Services Output and its Permanent Component

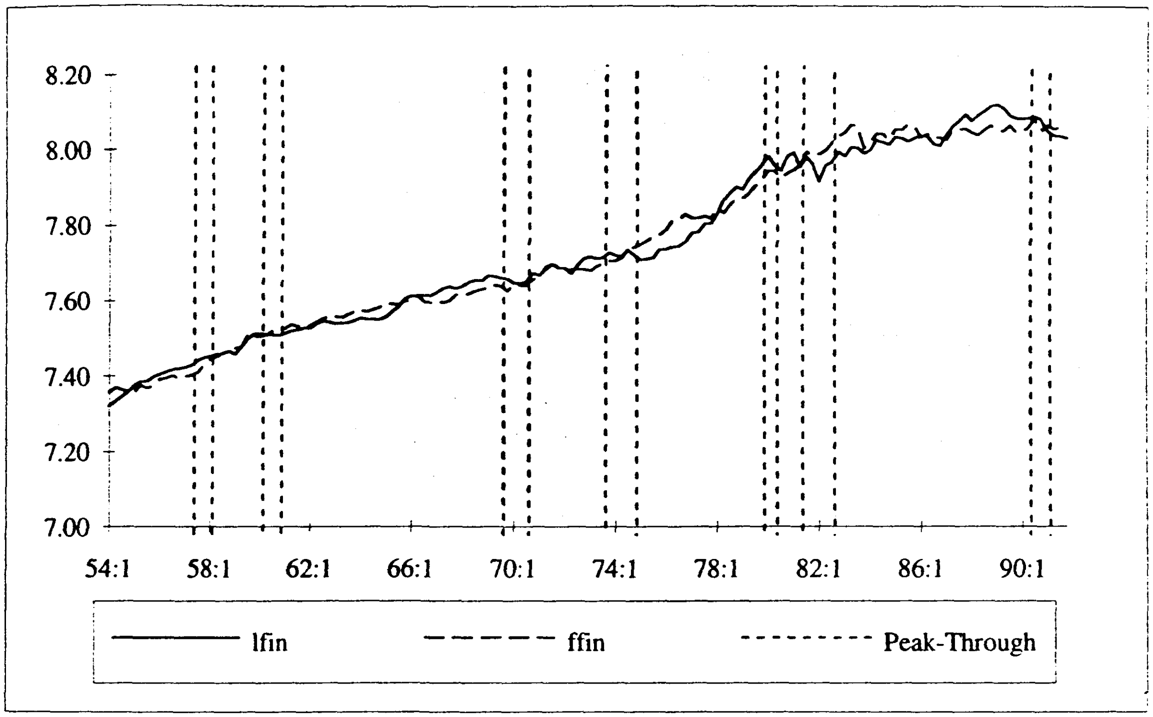


Figure 2-9b: Transitory Component of F.I.R.E.

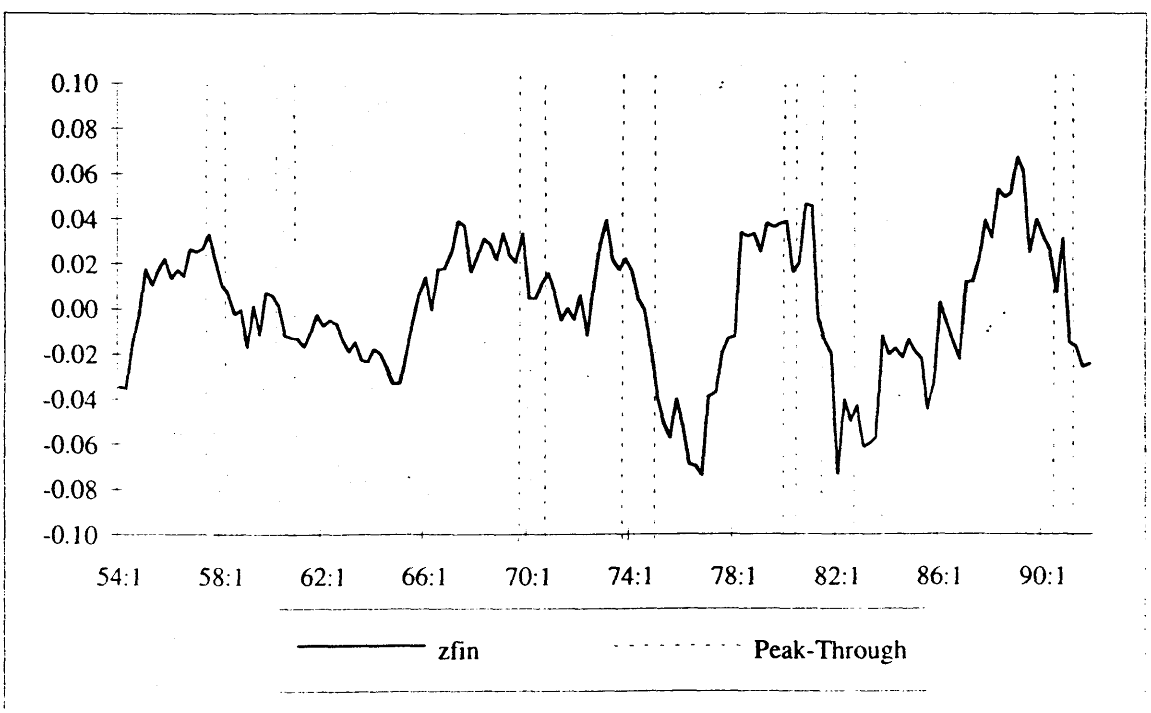


Figure 2-10a: Other Services Output and its Permanent Component

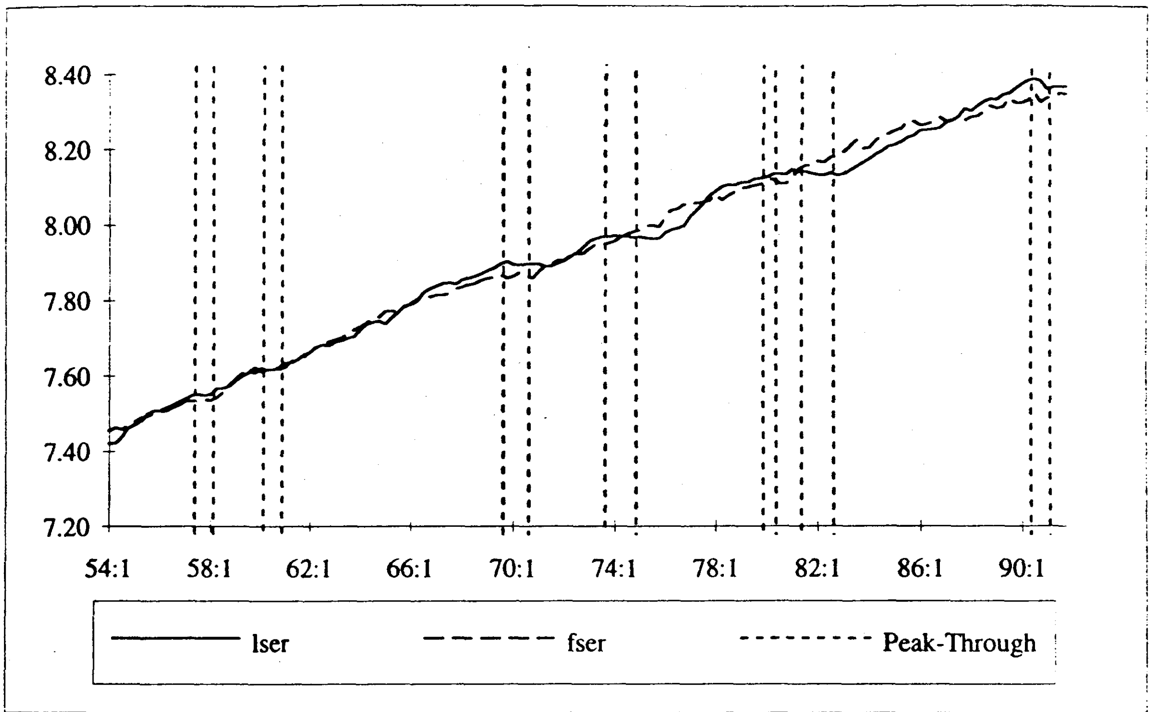


Figure 2-10b: Transitory Component of Other Services

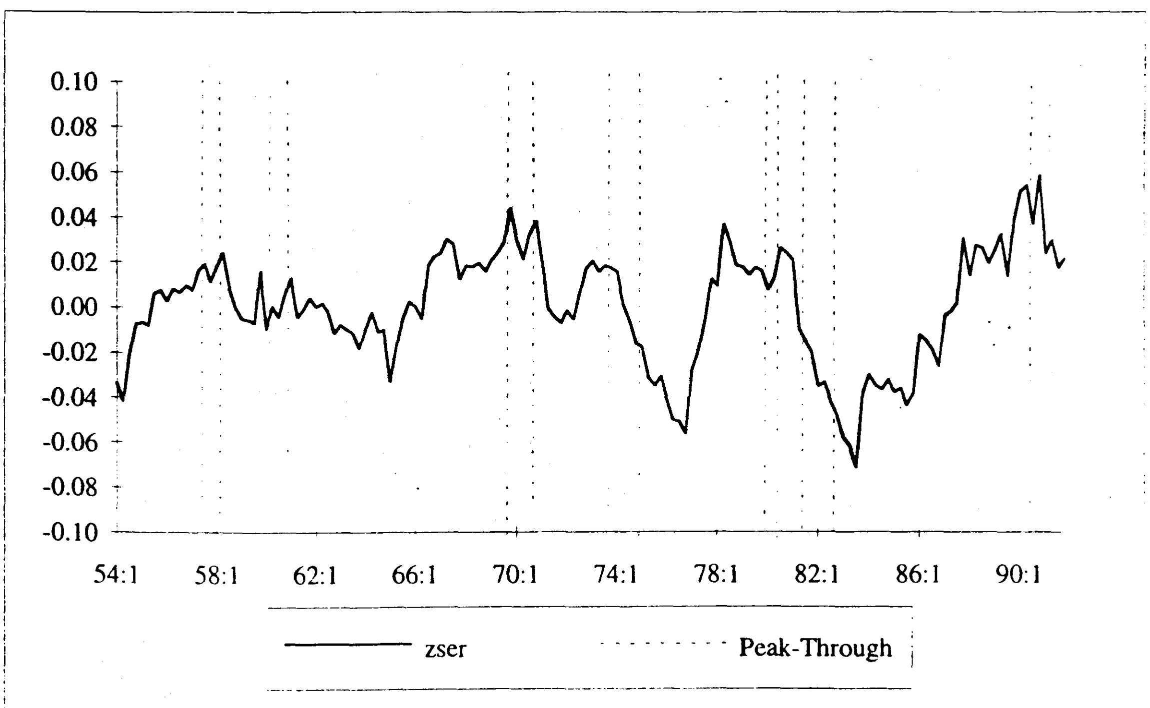


Figure 3a: Aggregate Output and its Permanent Component

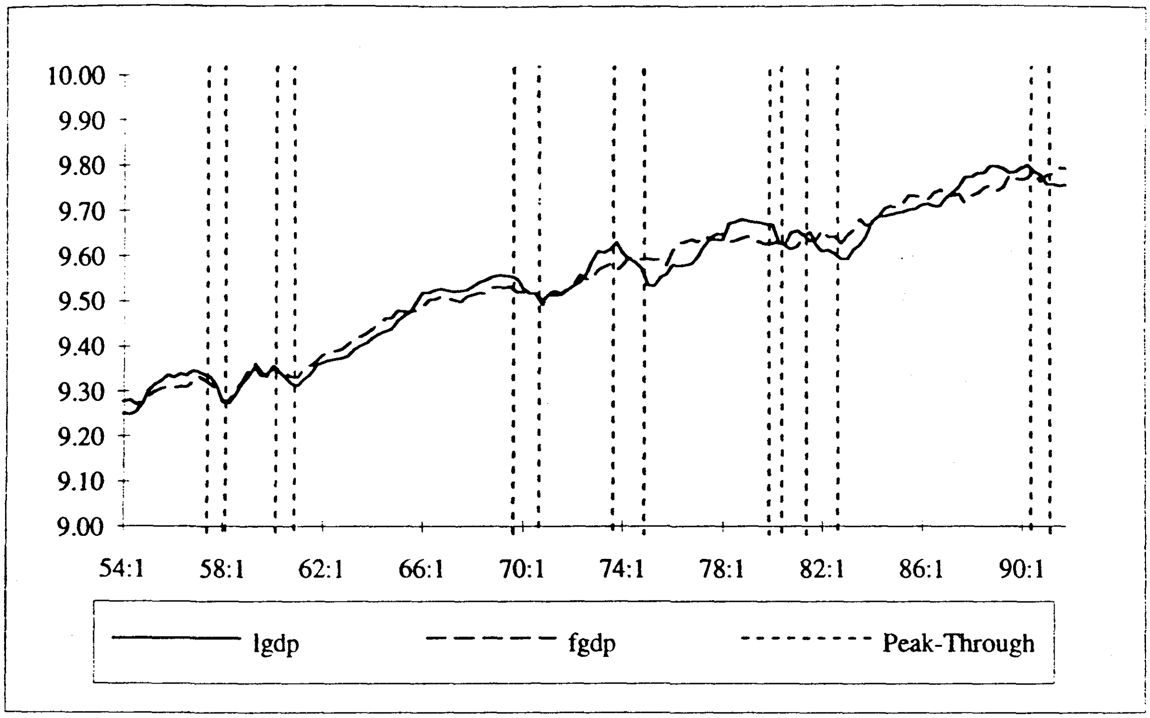


Figure 3b: Transitory Component of Aggregate Output

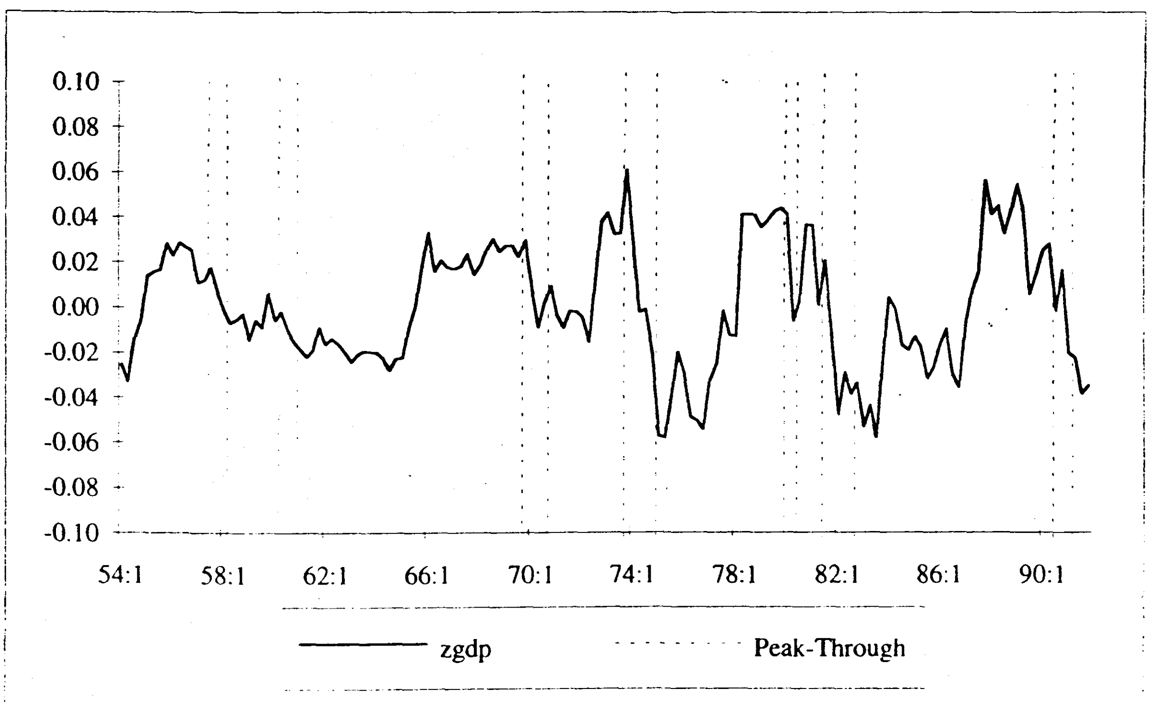


Figure 4-1: Responses of Agriculture to Permanent and Temporary Shocks

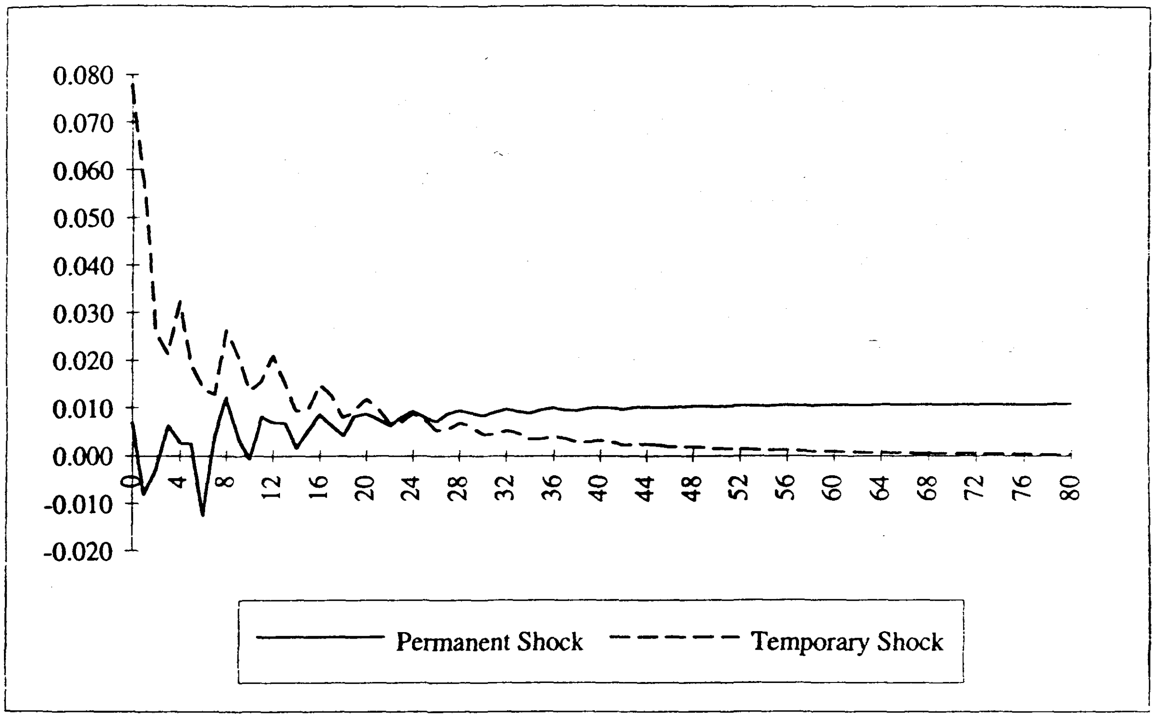


Figure 4-2: Responses of Mining to Permanent and Temporary Shocks

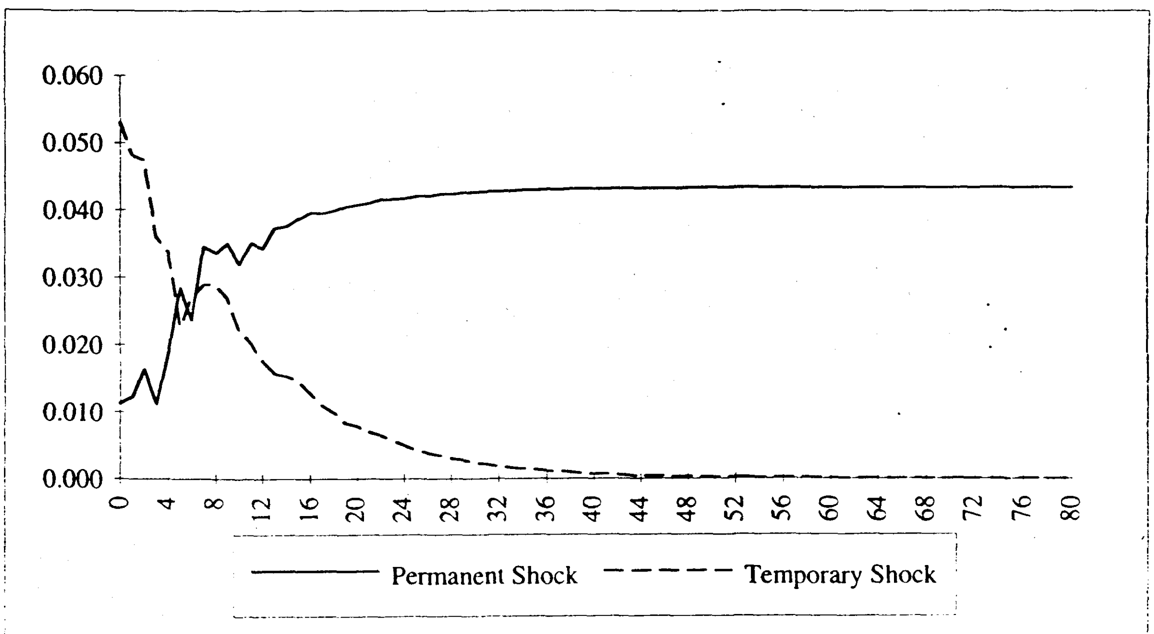


Figure 4-3: Responses of Construction to Permanent and Temporary Shocks

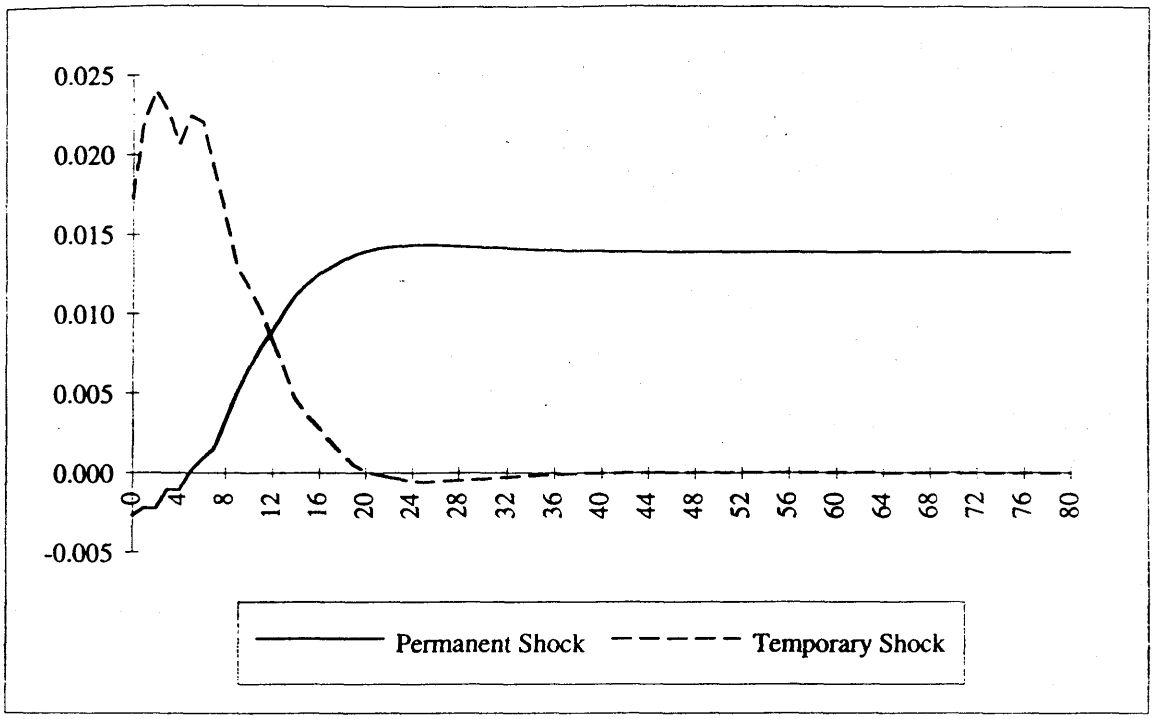


Figure 4-4: Responses of Durable Manufacturing to Permanent and Temporary Shocks

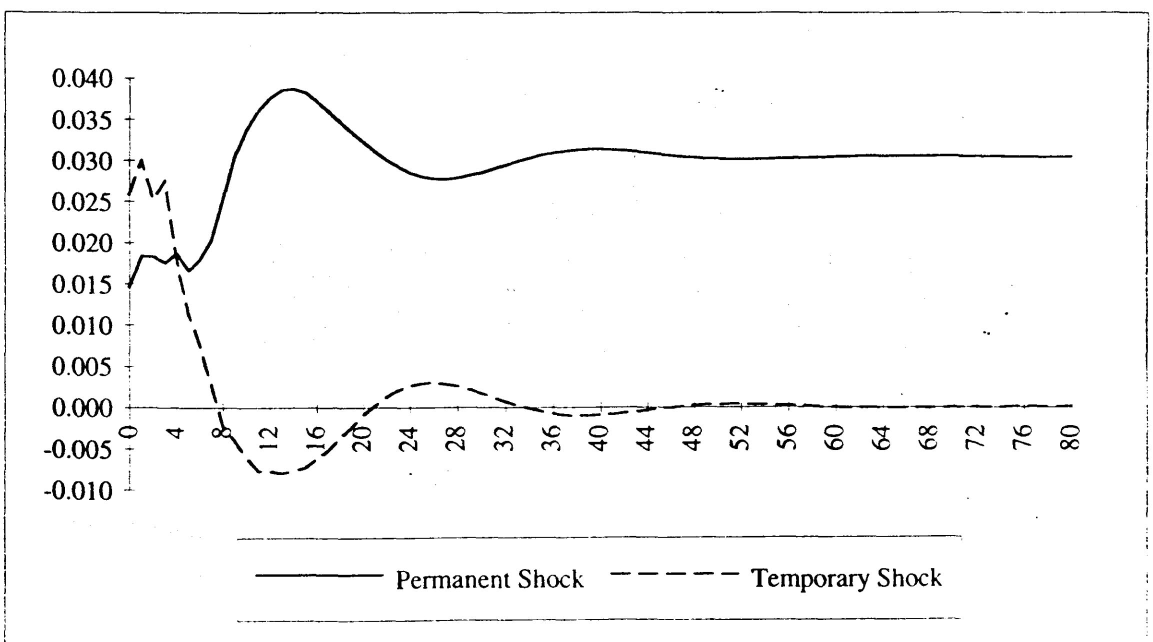


Figure 4-5: Responses of Non-durable Manufacturing to Permanent and Temporary Shocks

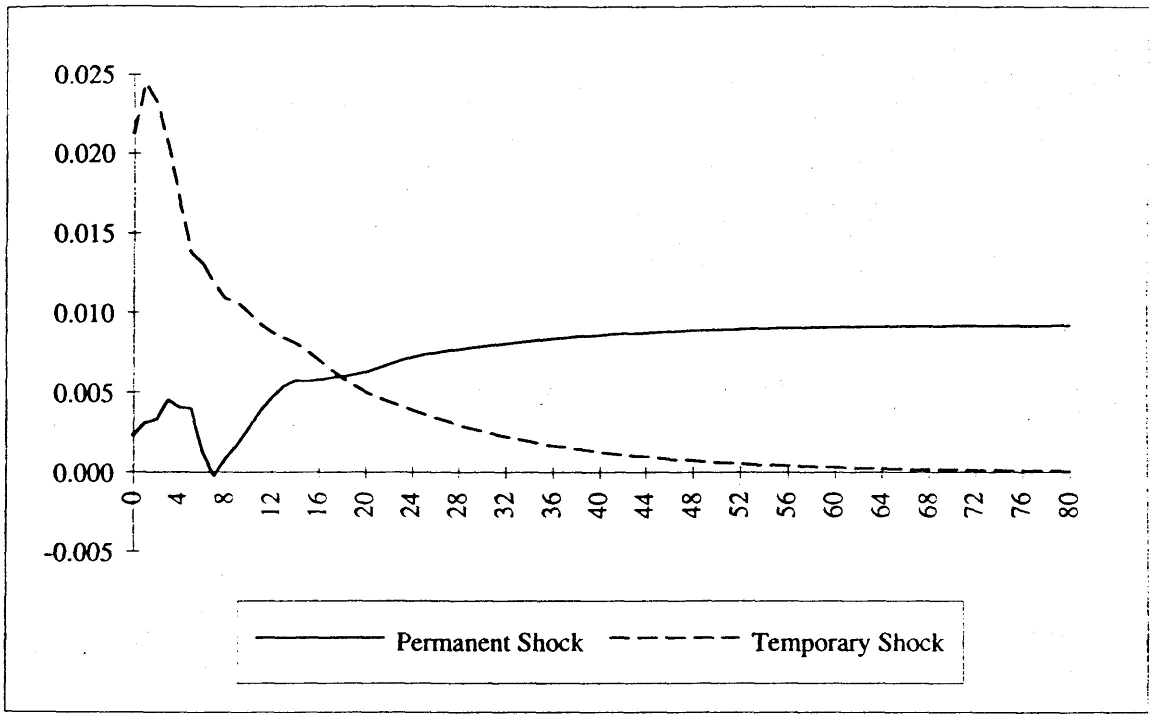


Figure 4-6: Responses of Trans. & Communication to Permanent and Temporary Shocks

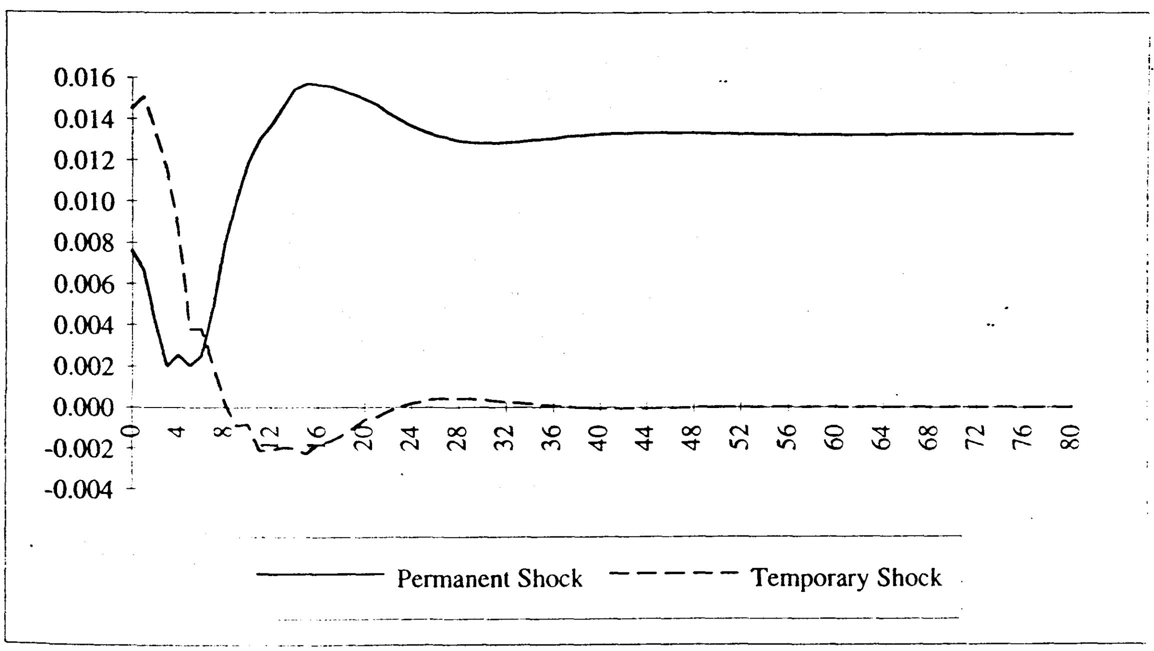


Figure 4-7: Responses of EG&S to Permanent and Temporary Shocks

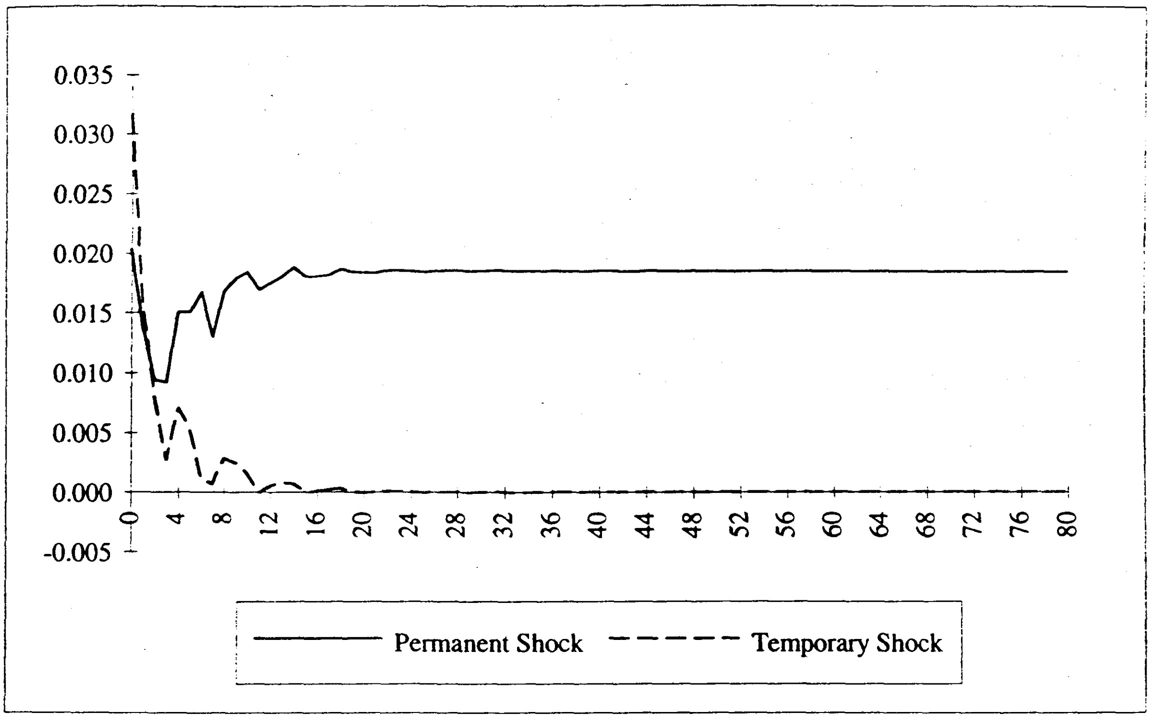


Figure 4-8: Responses of Domestic Trade to Permanent and Temporary Shocks

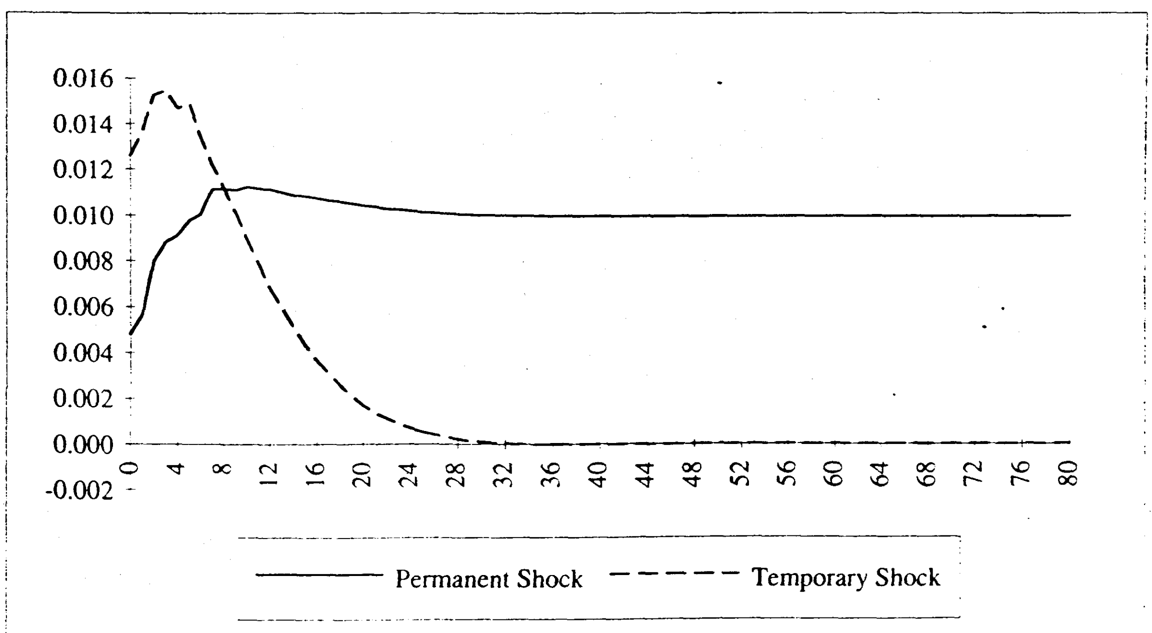


Figure 4-9: Responses of F.I.R.E. to Permanent and Temporary Shocks

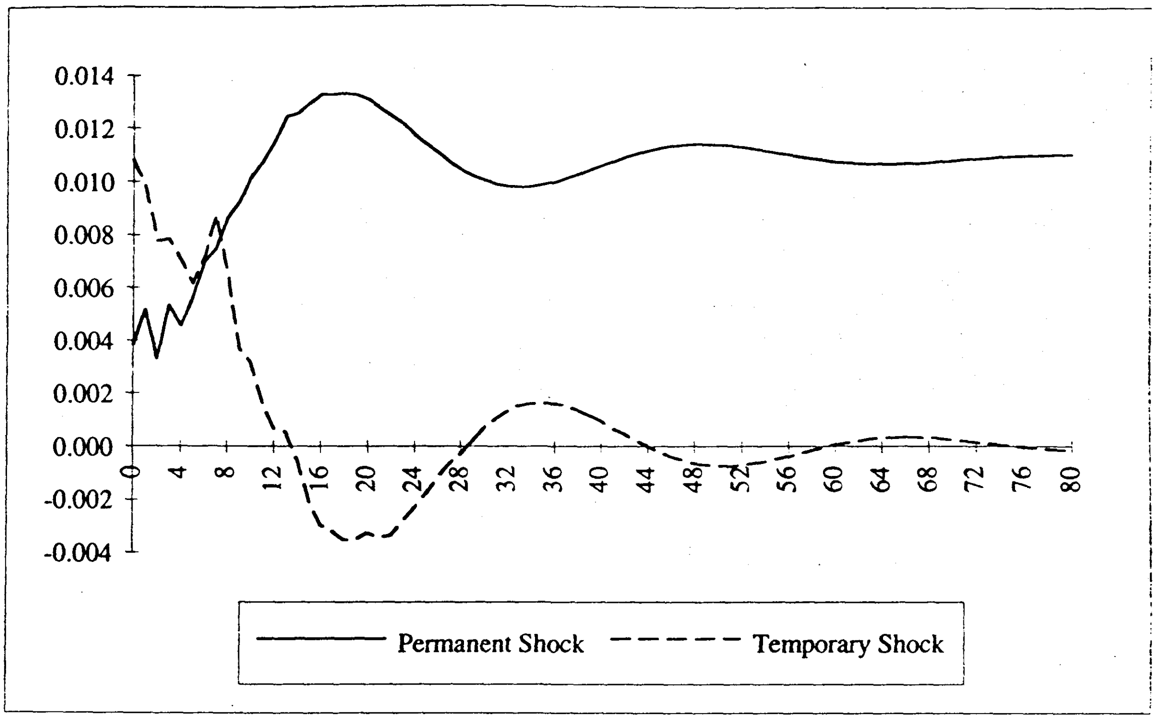


Figure 4-10: Responses of Other Services to Permanent and Temporary Shocks

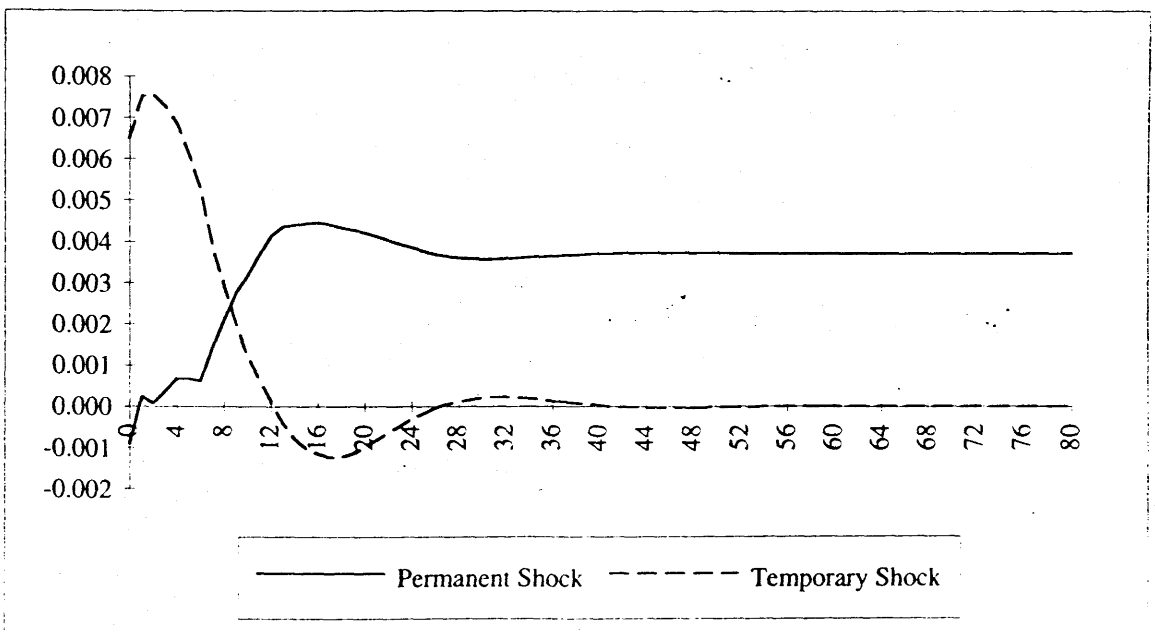


Figure 5: Responses of GDP to Permanent and Temporary Shocks

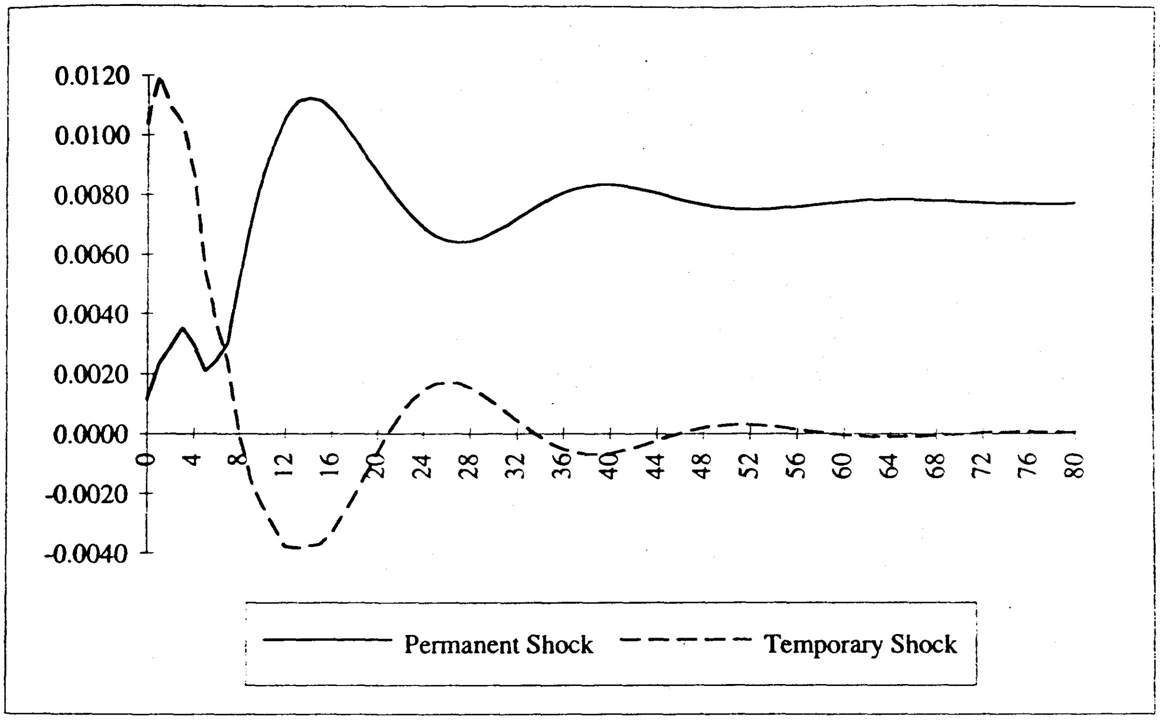


Figure 6: GDP, Its Permanent Component and Potential Income

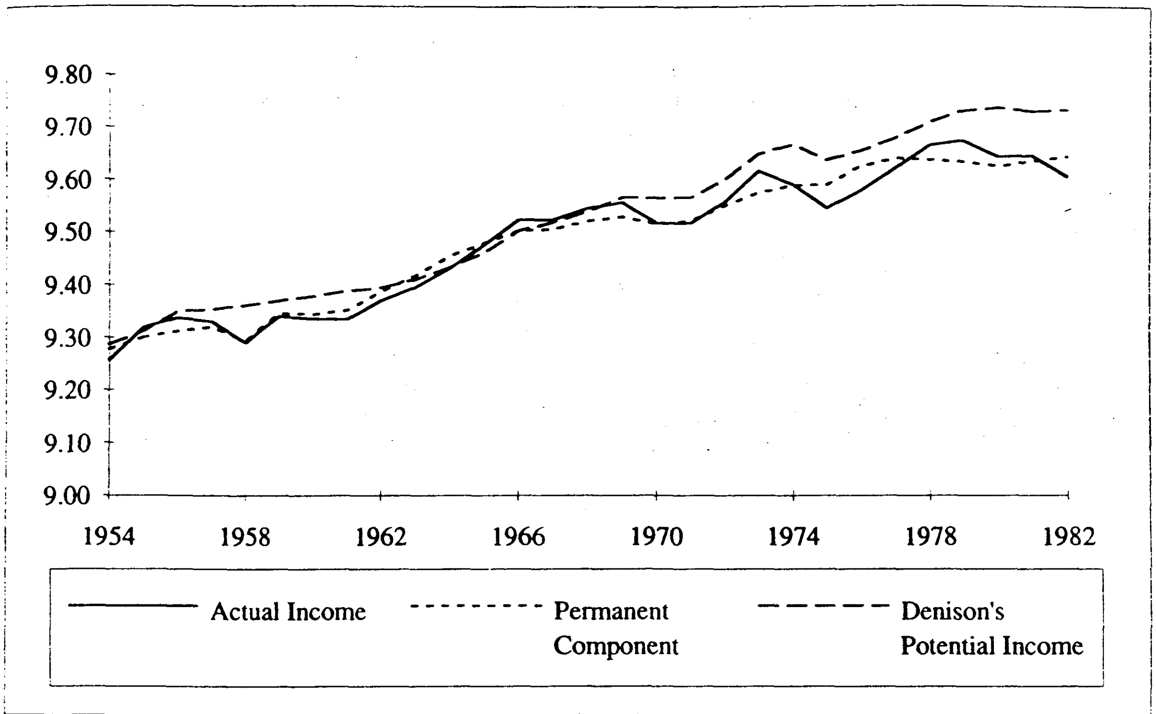


Figure 7: Productivity and Permanent Innovations to Non-durable Manufacturing

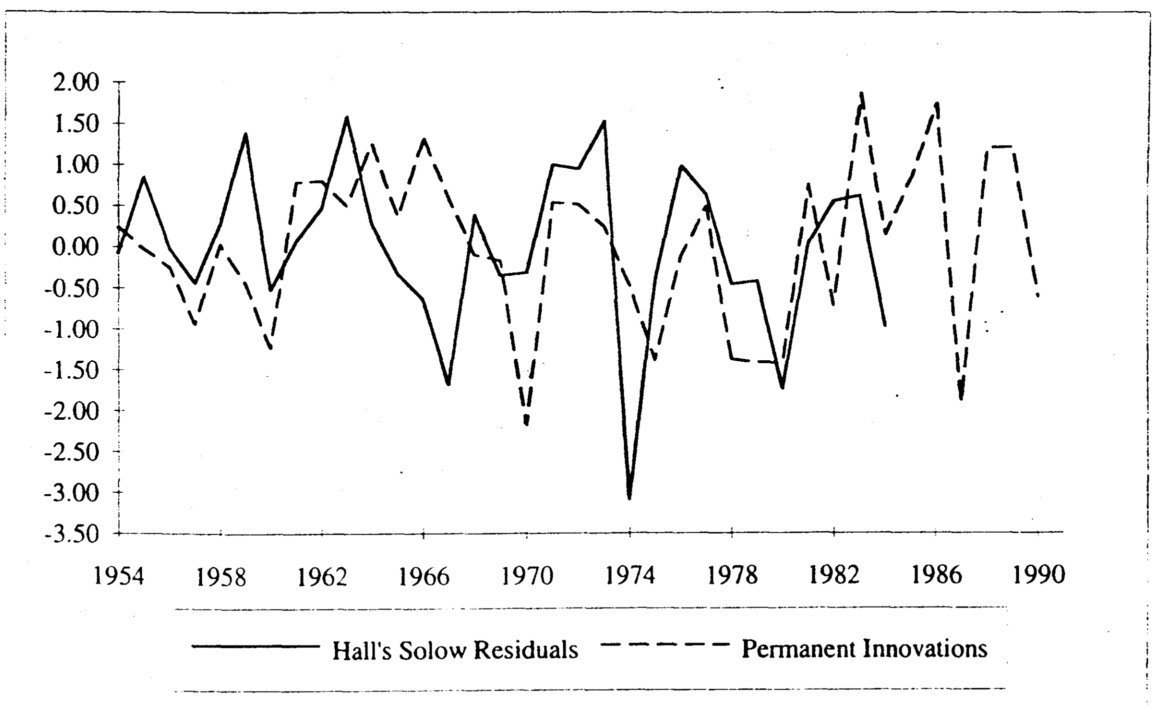
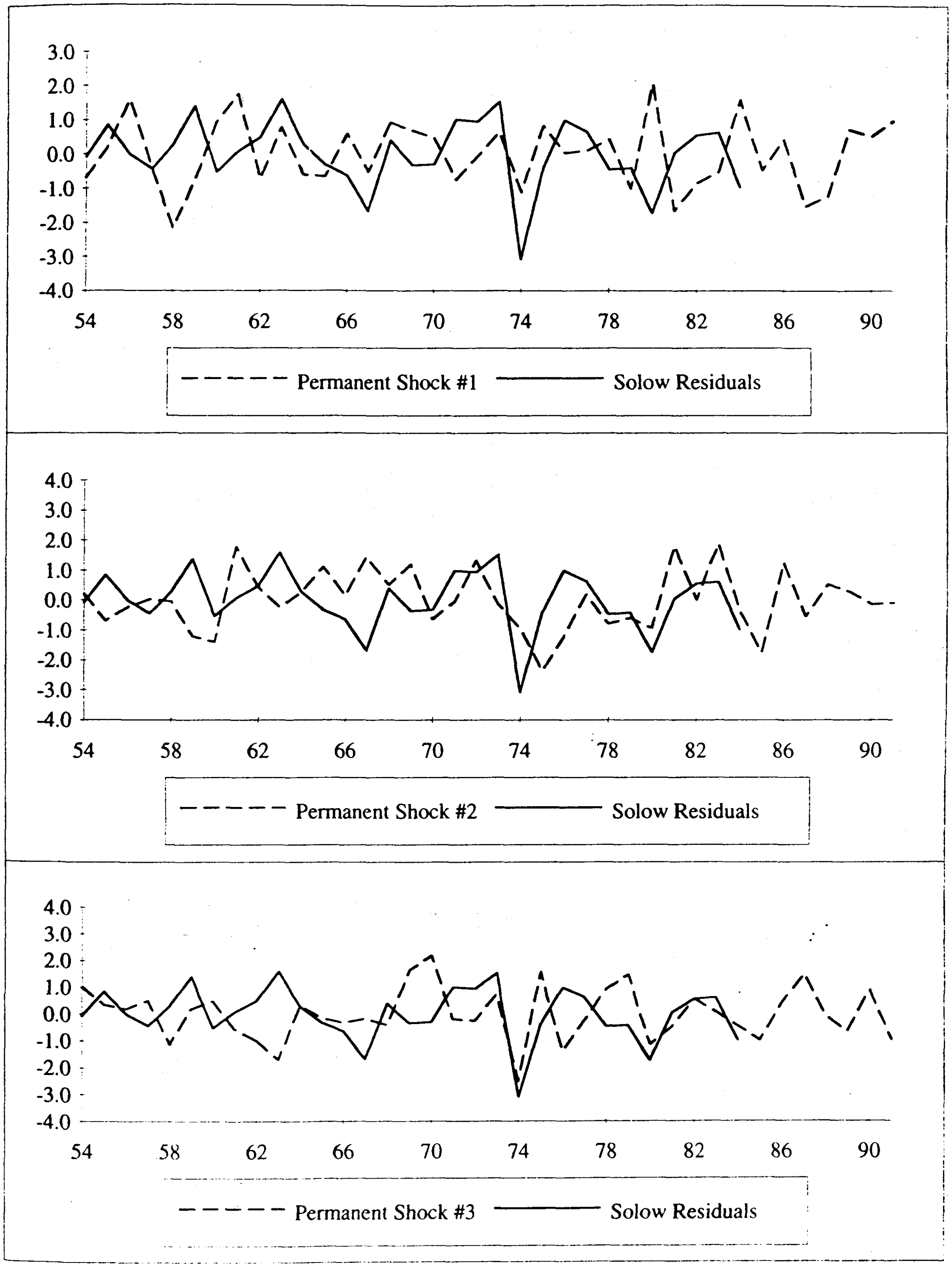


Figure 8: Permanent Shocks and Solow Residuals



Essay 2:

Decomposing Output and

Facts About Long- and Short-run Fluctuations

Abstract

This paper examines the sensivity of output fluctuations to different decomposition techniques. Typical analyses of fluctuations decompose output into a permanent and a transitory component and examine their characteristics at different frequencies. Since there is no consensus on how to subtract cycle from trend, different conclusions have been reached on the properties of both components. Using seven different procedures I decompose output and compare sample moments of long- and short-run fluctuations in output and persistence of shocks to both components. The results show that there are significant differences across techniques.

1. Introduction

The standard approach in macroeconomics textbooks separates long-run fluctuations from short-run fluctuations. This dichotomy is based on the main structure of the traditional Keynesian approach to macroeconomics where the economy is assumed to expand along a deterministic trend referred as "potential" level of output. The fluctuations around this long-run path or potential level constitute business cycles which are caused by factors independent of those that drive the growth of the economy. While all kinds of fluctuations are viewed as undesirable or even politically and socially dangerous; until the end of the 1960s, macroeconomists were only interested in fluctuations at business cycle frequencies. Forces that drive the economy in the long-run, such as population growth, capital accumulation or technical progress, were summarized as polynomials of time. Hence, empirical studies of macroeconomic fluctuations were mainly concerned to document facts about the movements around the deterministic trend in hope of being able to calculate the magnitude of such fluctuations and possibly to choose leading indicators to form policies in advance to reduce the amplitudes of cycles.

In early 1970s, the Keynesian approach was challenged on a theoretical basis for the way it viewed and explained fluctuations. New classical economics, originated from this strong criticism, asserted that shocks that cause fluctuations at business cycle frequencies may also affect the economy in the long-run. In extreme versions of real business cycles models (e.g., Prescott (1986)), it is claimed that all variations in output are attributable to real factors and hence demand policies have no effect on the economy or are merely responses of authorities to changes in real factors.

The theoretical challenge of the traditional view is accompanied by empirical findings of unit roots in many macroeconomic variables. Starting with the seminal paper by Nelson and Plosser (1982), the researchers have consistently failed to reject the hypothesis that many aggregate variables contain stochastic trends. The existence of unit roots in time series significantly altered the conventional decomposition in two different ways. First, elimination of the secular components cannot be accomplished by simple regression methods; and second, the idea that the variance of the trend is relatively small compared to the variance of the cyclical component cannot be maintained. Beveridge and Nelson (1981) developed a statistical decomposition based on the assumption of non-stationarity where the permanent component is highly volatile and perfectly correlated with the transitory component. Their work has been followed by Harvey (1985) and Watson (1986). While preserving the non-stationarity assumption, they proposed alternative statistical representations of permanent and transitory components where both components are assumed to be orthogonal to each other, and consequently reached different conclusions about the fluctuations in the economy.

Given the fact that there is very limited number of data points, it is not possible to determine which decomposition represents the true data generating mechanism. In particular, the choice of the relationship between the permanent and transitory components is arbitrary, depending upon the subjective orientation of the researcher. Therefore, the statistical decompositions to analyze macroeconomic fluctuations lack the necessary robustness to be reliable.

Another problem with decomposing time series into different frequency level components is raised by those who are concerned with the deficiency of statistical techniques not being based on an economic model. For example, King, Plosser, Stock and Watson (1991) and King, Plosser and Rebelo (1988) advocate decompositions that are based on economic models which provide guidelines about the mechanism generating fluctuations. Further, Kydland and Prescott (1990) consider economic theory as an organizing principle for time series analysis to investigate business cycle facts. However, economic theory neither specifies the shape of the trend nor asserts what kind of relationship should exist between the components. Without having some statistical facts about the variables used in the model, the decompositions obtained through economic models suffer the same arbitrariness and subjectivity as the statistical decompositions.

The discussion above leads us to the conclusion that we are facing a vicious circle. Various theories of macroeconomic fluctuations have different predictions about the nature of the economy and consequently suggest exclusive policies. To test these theories we need some sort of decomposition, yet every decomposition indicates different properties of the time series. The choice of "correct" representation of the components, then, calls for economic theory.

Nevertheless, this dilemma does not prevent economists from pursuit of better description of economic time seroes by separating the permanent component from the transitory one using various techniques. My goal in this paper is to examine properties of the permanent and transitory components of private real per capita output obtained by different decompositions. I do not claim that any of the models examined here are superior to the other. The idea is to document if there exist any robust finding independent of the technique used and provide new evidence for possible anomalies.

In this paper, I compare seven different decomposition procedures on private real per capita output which have been commonly used in the literature. I report statistical facts about the components of this series and provide graphical comparison. The next section briefly describes the decomposition procedures. The section with empirical results will be followed by concluding remarks.

2. Alternative Decomposition Techniques

This section provides a brief review of seven different procedures used in the literature to decompose time series into permanent and transitory components. Five of these techniques are univariate (polynomial functions of time (PFT), Hodrick-Prescott filter (HP), First Differences (FD), Beveridge-Nelson decomposition (BN) and unobserved components model (UC)) and two of them are multivariate (multivariate Beveridge-Nelson decomposition (MBN) and Gonzalo-Granger decomposition (GG)). Four procedures assume that both components are unobservable and can be identified through a set of statistical assumptions (PFT, FD, BN and UC), while the other three (HP, MBN and GG) are based either on an economic model or preferences of the researcher.

Throughout this section the observed time series is denoted as X_t. A permanent-transitory decomposition is required to satisfy the following condition:

$$X_t = P_t + T_t \tag{1}$$

where P_t is the permanent component and T_t is the transitory component. As it will be clear later, each procedure needs some additional assumptions to identify the components. I assume that X_t does not contain any seasonal components or has previously been adjusted for seasonal fluctuations. This assumption is not without any consequences, but, for all practical purposes, I ignore here any mishandled seasonality.

Polynomial Functions of Time

The first procedure I examine is different from the other six in that it assumes that X_t is a stationary process around a deterministic trend. This is the oldest and simplest procedure among all and used in many traditional analyses before 1980s. It assumes that the trend and cyclical components are uncorrelated and the secular component is a deterministic process which can be approximated by polynomial functions of time:

$$P_t = a + \sum_{j=1}^{q} b_{kj} f_j (t - \bar{t}_k) \qquad \text{for } \ \bar{t}_k + 1 \le t \le T \tag{2}$$

where q is usually chosen to be a small integer. The above equation also allows for breaks in the trend at a known time $\bar{t}_k$ with k being the number of such breaks. The estimate of the permanent component is obtained by regressing X_t on a constant and polynomial functions of time and by taking the predicted value. Then the transitory component is defined as:

$$T_t = X_t - P_t. \tag{3}$$

In this paper, I consider two specifications for this method. The first one is a linear trend model (LIN) with no breaks. The second specification considers a break in the secular component at 1973:3 and hence is a segmented trend model (SEG).

Hodrick-Prescott Filter

Among the univariate procedures, only Hodrick-Prescott filter goes beyond from being a statistical exercise. It assumes that the trend is not something inherent to the data but rather a representation of the preferences of the researcher and depends on the question being investigated. The researcher will extract a rather different trend if she is interested in long cycles as opposed to the short ones. It is this flexibility which makes HP filter very popular among empirical macroeconomists. The selection of the trend component, however, is a question of curve fitting since the trend estimated by HP filter resembles a rough, hand-drawn line by the researcher herself. In that sense the estimate of permanent component is a smooth stochastic process and uncorrelated with the transitory component.

The estimate of the trend is obtained by solving the following problem (Hodrick and Prescott (1980)):

$$\min_{\{P_t\}_{t=1}^{N}} \sum_{t=1}^{N}(X_t - P_t)^2 + s\sum_{t=1}^{N}[(P_t - P_{t-1}) - (P_{t+1} - P_t)]^2 \tag{4}$$

where N is the number of observations and s is the smoothing factor which penalizes excess variability in the trend. Notice that the smoothing factor s is not estimated from the data. It is selected a priori by the researcher depending upon her preferences or the question she investigates. When s gets larger, the penalty on large fluctuations in the permanent component increases. The optimal value of s is obtained from a signal extraction framework and is the ratio of the variance of the trend to the transitory component. Yet Hodrick and Prescott suggest a value of 1600 for quarterly data and 4 for annual data. For comparison purposes, I used both values and denoted the first as HP1600 and the second as HP4.

First Differences

At the beginning of 1980s a major break occurred in analyzing economic time series. Starting with the seminal paper by Nelson and Plosser (1982), a large number of studies have shown that the tests cannot reject the hypothesis that many components of economic activity contain a unit root or a stochastic trend. Therefore, any decomposition of economic variables has to deal with the non-stationarity of the observed time series. The easiest way to decompose a time-series by taking into account of its non-stationarity is to assume that X_t is a random walk with drift:

$$X_t = a + X_{t-1} + \varepsilon_t \tag{5}$$

In this model the non-stationarity of X_t is entirely due to the permanent component and the estimate of the transitory component is:

$$T_t = \varepsilon_t. \tag{6}$$

Beveridge-Nelson Decomposition

A more sophisticated decomposition under the assumption of non-stationarity is developed by Beveridge and Nelson (1981). The key assumption of this procedure is that the permanent component is a pure random walk and the transitory component is a stationary process. Since X_t is integrated of order one, I(1), its first differences are stationary and assumed to follow an ARMA process:

$$\phi(L)\Delta X_t = \mu + \theta(L)\varepsilon_t \tag{7}$$

where $\Delta \equiv 1 - L$, L is the lag operator, $\phi(L)$ and $\theta(L)$ are polynomials of order p and q respectively and $\varepsilon_t \sim iid(0, \sigma^2)$. The moving average representation of ΔX_t exists and can be written as:

$$\Delta X_t = \bar{\mu} + \varphi(L)\varepsilon_t \tag{8}$$

where $\bar{\mu} = \dfrac{\mu}{\varphi(1)}$, $\varphi(L) = \phi(L)^{-1}\theta(L)$ and $\phi(1) = 1 - \sum_{j=1}^{p-1}\phi_j$.

Beveridge and Nelson base their concept of decomposition on the relation between the current value of X_t and its future forecast profile. Notice that the expectation of X_{t+k} conditional on the values of X_t through t is:

$$E(X_{t+k} \mid X_t, X_{t-1}, \ldots) = X_t + E(\Delta X_{t+1} + \Delta X_{t+2} + \ldots + \Delta X_{t+k} \mid \Delta X_t, \Delta X_{t-1}, \ldots) \tag{9}$$

since X_t is the sum of all ΔX's. From (8), however,

$$E(\Delta X_{t+k} \mid \Delta X_t, \Delta X_{t-1}, \ldots) = \bar{\mu} + \sum_{j=1}^{k} \varphi_j \varepsilon_{t+1-j}, \tag{10}$$

and Equations (7) and (8) reduces to:

$$E(X_{t+k} \mid X_t, X_{t-1}, \ldots) = X_0 + k\bar{\mu} + \left(\sum_{j=1}^{\infty} \varphi_j\right)\varepsilon_t + \left(\sum_{j=2}^{\infty} \varphi_j\right)\varepsilon_{t-1} + \ldots \tag{11}$$

with X_0 being a constant when k goes to infinity, and $k\bar{\mu}$ is the deterministic path of the process. The permanent component is then defined as the long-run forecast of X_t such that:

$$P_t - P_{t-1} = \bar{\mu} + \left(\sum_{j=0}^{\infty} \varphi_j\right)\varepsilon_t \quad \text{with} \quad \varphi_0 \equiv 1 \tag{12}$$

and the transitory component is:

$$T_t = \sum_{i=0}^{\infty}\left(\sum_{j=i+1}^{\infty} \varphi_j\right)\varepsilon_{t-i} \tag{13}$$

There are two important features of the Beveridge-Nelson decomposition. First, since the innovations to both permanent and transitory components are the same, they are perfectly correlated. This means that there is only one type of shock in the economy which has both permanent and temporary consequences. Some versions of real business cycles approach to macroeconomic fluctuations claims that this sole shock in the economy is attributable to real factors.

The second feature of the Beveridge-Nelson decomposition is that it relies on a specific ARIMA model. However, many different specifications of ARIMA models fit the data very well, and although all of them have very similar short-run dynamics, the long-run features of each specification are considerably dissimilar. Two researchers working on the same time series may end up with completely different results if they choose different but equally well fitting specifications. In this paper, for comparison purposes, I choose the order of both p and q by using the Akaike Information Criteria (AIC). The best specification according to the AIC is that both p and q are equal to three. However, the results for various specifications are also available upon request.

Unobserved Components Model

The perfect correlation of permanent and transitory components of Beveridge-Nelson decomposition is challenged by many authors in that it oversimplifies the economic activity. As an alternative a "negative" version of it has been developed by Harvey (1985) and Watson (1986) among others, where the innovations to the components are assumed to be completely orthogonal. The main assumptions of Beveridge-Nelson decomposition that the permanent component is a random walk and the transitory component is a stationary process are still maintained. However, in the literature, standard applications of unobserved components model assume that the transitory component follows an AR(2) process. The model is based upon the following assumptions along Equation (1):

$$P_t = \mu + P_{t-1} + u_t \tag{14}$$

$$\Phi(L)T_t = v_t \tag{15}$$

where u_t and v_t are independent white noise processes with finite variances, σ_u^2 and σ_v^2 respectively. The model is then estimated by using state space techniques to find the likelihood of the sample given the values of σ_u^2, σ_v^2 and coefficients of $\Phi(L)$. For example, if $\Phi(L)$ is order two the state equation is:

$$w_t = Aw_{t-1} + u_t \qquad (16)$$

and the measurement equation is:

$$z_t = Hw_t + v_t \qquad (17)$$

where $w_t=[P_t\ P_{t-1}\ P_{t-2}\ \mu]'$ and $z_t=X_t-\phi_1 X_{t-1}-\phi_2 X_{t-2}$. The maximum likelihood estimates of the parameters in the system can be found by starting with an initial guess for the state vector and its covariance matrix and then recursively applying the Kalman prediction and updating equations. I estimated the unobserved components model in its standard form, i.e., choosing the starting values of the state covariance matrix as a diagonal matrix with large values and assuming that the transitory component is a stationary AR(2) process. To preserve the comparability with other procedures I did not use recursive smoothing. Therefore the estimate of unobserved components model, I am using here, are one-sided as the other procedures in this paper.

Multivariate Beveridge-Nelson Decomposition

All the univariate procedures except the Hodrick-Prescott filter discussed above are criticized as "measurement without theory". They are just statistical procedures without being backed up by an economic model, yet all of them have very strong and significantly different implications about the economic activity. Therefore, it is argued that before applying different techniques and reporting facts, one has to have a theory that explains the data generating mechanism of the observed series. King, Plosser, Stock and Watson (1991), among others, advocating this view, propose a model where all the endogenous variables are driven by the same technology shock in the long-run.

The statistical model of MBN decomposition is based on the fact that cointegrating multiple time series share at least one common stochastic trend. Stock and Watson (1988) prove that if there exists a cointegration matrix which reduces all variables in the system simultaneously to stationary processes, then there exists a common stochastic trend. The decomposition of variables into permanent and transitory components, then, follows the estimation of stochastic trends and cointegrating vectors in the system. As in the univariate framework, the permanent components of the variables are assumed to be random walks and the innovations to both components to be perfectly correlated.

Let X_t be an p×1 vector of time series, then the vector error correction representation of X_t can be written as:

$$\Delta X_t = \mu + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-k} + \varepsilon_t \tag{18}$$

where $\Pi = \alpha\beta'$ and $\varepsilon_t \sim iid(0,\Omega)$. Assuming that the moving average representation exists, Equation (18) can be represented in the following form:

$$\Delta X_t = \bar{\mu} + \Psi(L)\varepsilon_t \tag{19}$$

Following Beveridge and Nelson and as proven in Johansen (1991), the process X_t which satisfy Equation (19) has the following representation:

$$X_t = X_0 + \Psi(1)\bar{\mu}t + \Psi(1)\left(\sum_{i=1}^{t} \varepsilon_i\right) + \tilde{\Psi}(L)\left(\sum_{i=1}^{t} \varepsilon_i\right) \tag{20}$$

where $\tilde{\Psi}(L) = \dfrac{(\Psi(L) - \Psi(1))}{(1-L)}$. The permanent component of X_t is then a random walk process of the form:

$$P_t = X_0 + \Psi(1)\bar{\mu}t + \Psi(1)\left(\sum_{i=1}^{t} \varepsilon_i\right) \tag{21}$$

and the transitory component is:

$$T_t = \tilde{\Psi}(L)\left(\sum_{i=1}^{t} \varepsilon_i\right) \tag{22}$$

For multivariate Beveridge-Nelson decomposition I used the model suggested in King, Plosser, Stock and Watson (1991). The three variables included in the model are output, consumption and investment. First I tested whether any cointegration relationship exists between the variables in the model and concluded that there are two of them. The test result implies that there is only one stochastic trend. Based on this information using Equations (21) and (22) I decomposed each series into a permanent and a transitory component. As in the univariate version of the model, the estimation of components depends on the choice of lag structure. I used eight lags of levels of the variables which, I assume, fairly captures the dynamics of quarterly observations.

Gonzalo-Granger Decomposition

Gonzalo-Granger decomposition like MBN capitalizes on the cointegration properties of the data. The procedure proposed by Gonzalo and Granger (1992) differs from the previous ones in two ways. First it allows the permanent component to be an ARIMA process. While being a suitable identifying assumption for statistical decomposition, the requirement of the permanent component to be a random walk has ambiguous economic interpretation. Lippi and Reichlin (1989) points out that if one views the trend as productivity, then this assumption imposes certain doubtful restriction on the technical change process. For example, it ignores any learning at the firm level and assumes that the change is absorbed simultaneously by all firms. Therefore, by allowing the growth of permanent component to be serially correlated, the Gonzalo-Granger decomposition captures richer dynamics than that captured by the random walk models. The second feature of this procedure is that it allows the innovations to the components to be imperfectly correlated.

To identify the components, the GG procedure requires conventional assumptions, (i.e., the permanent component is non-stationary and transitory component is stationary, and the variances of the transitory component and changes in the permanent component to be non-zero) along the assumption that the only shocks that can affect the long-run forecast of X_t are the ones coming from the innovations to the permanent component.

The estimation of the components is based on Equation (18) as MBN decomposition. First the common factors, f_t, which drive the system are assumed to be linear combinations of the variables in X_t. Since $z_t = \beta' X_t$ is stationary, then one only needs to show which linear combination of X_t makes z_t have no long-run impact on X_t. An obvious candidate is $\alpha_\perp{}' X_t$. Once common factors are estimated then the common factor model can be written as:

$$X_t = A_1 \alpha_\perp{}' X_t + A_2 \beta' X_t \tag{23}$$

The first expression on the right hand side of (21) is identified as the permanent component and the last expression as the transitory component.

For Gonzalo-Granger decomposition I used the same model as for the multivariate Beveridge-Nelson decomposition and exploited the same cointegration relationships among output, consumption and investment. The lag length is again chosen to be eight in levels.

3. Results

In this section I present results obtained using the logarithm of seasonally adjusted quarterly US time series. The sample starts from 1954:1 to avoid the influence of the Korean War, the Fed accord and price controls and runs through 1992:4. The variables used in this paper are available in Citibase and are per capita real private GNP [Citibase mnemonics: GNPQ-GGEQ], per capita consumption expenditures on non-durables and services [GCNQ+GSCQ] and real per capita fixed investment in plants and equipments plus durables [GINPDQ+GCDQ]. To obtain per capita figures total civilian non-institutional population [P16] is used.

Figure 1 presents the plots of the logarithm of the private per capita real GNP and its permanent component obtained by various decomposition techniques. There are two important features worth to note. First, the permanent components in three models (HP4, BN and FD) are very close to the original series, whereas the permanent components in the other procedures smooth the series considerably. Second, the permanent components in univariate models show uniform behavior through the NBER designated recessions. For example, in HP4, FD, BN, and UC models the trend shows a decline when the economy hits a recession, and in LIN, SEG and HP1600, the secular component increases monotonically. However, both multivariate models (GG and MBN) produce permanent components whose behavior changes from recession to recession. To capture this difference between univariate and multivariate techniques it is instructive to examine the 1973-74 and 1981-82 recessions. While during the former period the secular components of multivariate decompositions decline, in the latter recession they move upwards. The permanent components in univariate analysis however indicate a uniform behavior during both recessions, they either decline or continue to grow. If the multivariate decompositions represent the true generating mechanism, then one can claim that 'business cycles' are not alike, in the sense that sometimes it is a permanent shock which causes a recession while at other times recessions are only a temporary movement from the potential level of output.

The estimates of transitory components are plotted in Figure 2. There are three groups with significant differences in length of cycles, level of cyclical amplitude and in matching the NBER chronology. In the first group, linear detrending (LIN) and multivariate (MBN and GG) procedures exhibit longer cycles with higher amplitudes and conform the NBER dating. Segmented detrending (SEG), HP1600 filter and unobserved components model (UC) constitute the second group. The cycle lengths of these transitory components are 4-6 years and the amplitudes of the cycles are almost half of the first group. They also match NBER peaks and throughs. Finally, HP4 filter, first differencing (FD) and Beveridge-Nelson decomposition (BN) produce very short and erratic cycles. The amplitudes of these cycles are extremely low and they have little agreement, if any, with NBER designated recessions.

There are a few conclusions that can be drawn from these graphs. First, the behaviors of different permanent components imply that a recession might be due to negative permanent shocks (HP4, FD, BN and UC) or due to temporary shocks only (LIN, SEG and HP1600) or due to both types of shocks (MBN and GG), depending on the procedure employed to analyze fluctuations. Second, the length and amplitude of transitory movements show variation across procedures used to decompose output. Third, different techniques imply different timing of peaks and throughs for cyclical fluctuations.

To support these observations statistically, I continue by comparing moments of the distribution of different permanent and transitory components. Table 1 reports the standard deviations of changes in permanent and transitory components, respectively.

The first line in Table 1 gives the mean and standard deviation of changes in log output, i.e., the growth rate of output. While average changes in permanent components are very close to each other and to the one of the output, the variances of changes in permanent components are quite different. Both HP filters smooth the series excessively, and hence have smaller variance. At the other extreme, the growth of the permanent components of first differencing and Beveridge-Nelson decomposition exhibit same or higher standard deviations than the original series.

The third column in Table 1 presents the standard deviations of various transitory components. Linear detrending procedure and multivariate models yield highest standard errors for transitory components ranging from $3.05*10^{-2}$ to $4.52*10^{-2}$. They are followed by SEG, HP1600 and UC with a standard deviation of around $2.5*10^{-2}$. The smallest variance is obtained for the transitory component of HP4 filter and it is very close to the variances of the transitory components of FD and BN. The largest standard deviation of an estimated transitory component (LIN) is seven times higher than the smallest (HP4). These results confirm what is seen in the graphs. The transitory components with longer cycles and higher amplitudes show higher variation and the volatility of cyclical components varies widely.

The literature which analyzes facts about business cycles reports only second moments. This common practice relies on the assumption that the cycles are normally distributed stochastic processes and therefore higher moments do not convey any information about the properties of the cycles. However, for a very long time economists discussed possible asymmetric behavior in macroeconomic fluctuations. For example, as early as 1936, Keynes stated that "the substitution of a downward for an upward tendency often takes place suddenly and violently . . . no such sharp turning point occurs when an upward is substituted for a downward tendency." Indeed, recently Neftci (1984) reported significant evidence in favor of cyclical asymmetry in various macroeconomic variables. Following his work, DeLong and Summers (1986), Blanchard and Watson (1986) and Sichel (1987) used higher moments to test the normality assumption of cycles in real output. Here, I compare the skewness coefficient and excess kurtosis of the components of output derived using different decomposition techniques to test asymmetric behavior and fat tails in their distributions.

The third moment, the coefficient of skewness, is used in the literature to detect two types of asymmetry. Following Sichel's (1987) terminology, the skewness coefficient of first differenced series shows "steepness" and the skewness coefficient of the series itself indicates "deepness". A negative coefficient implies that the contractions are steeper or deeper than the expansions, respectively. The fourth moment, or excess kurtosis, the difference between the coefficient of kurtosis if the distribution was normal and the estimated coefficient of kurtosis, is the indicator of whether the shocks to the components are frequent and small or not. A positive value means that the shocks are substantially large and do not happen very often.

Table 3 presents the coefficients of skewness and excess kurtosis. The reader should be warned about some technical details. Figures reported in Table 3 are not conditioned on any recession dating since, as discussed above, each procedure yields different timing for contractions and expansions. While in the literature only asymmetry at cyclical frequencies is examined, I also provide information about the asymmetry in permanent components. Yet, because these series are non-stationary I tested only their steepness. Moreover, since the tests for both moments are invalid in the presence of serial correlation, I performed Monte Carlo experiments to obtain standard errors of the coefficients as discussed in DeLong and Summers (1986).

The first two columns of Table 2 show the steepness and excess kurtosis of the growth rates of output and its different permanent components. Output shows significant negative skewness and leptokurtic behavior. The same result is also obtained for the changes in three permanent components (FD, BN and UC) which assume that the secular component is a random walk process. HP4 filter also exhibits steep contractions in the permanent component, but there is no evidence that the shocks to this trend are large.

Except LIN, transitory components obtained using univariate procedures exhibit significant deepness. The contractions of the transitory components of SEG and both HP filters are also steep. The only univariate procedure for which there is no evidence of deepness (LIN), however, has also steep contractions. Excess kurtosis is found only for the transitory components of HP4, FD and UC. Except these three, the statistics show that transitory shocks are small and frequent. These results are not observed for multivariate procedures. Both the coefficients of skewness and excess kurtosis are insignificant for the transitory components of these procedures. The evidence of no asymmetry and leptokurtic pattern indicates that the normality assumption holds for these two cases.

Finally, I analyze the persistence in the components of GNP. It is one of the important issues in the debate between Keynesian and neo-classical approach. Keynesian analysis claims that the shocks to output are transitory and turn back to the trend level after a short period of time. On the other hand, the neo-classical economists argue that the shocks to output do not dissipate in such a short time and actually prevail into the future infinitely. Contrary to the traditional view that there is little or no permanent effect, almost all recent studies have shown that output shocks are highly persistent. Yet there is major disagreement about the size of persistence. For example, Campbell and Mankiw (1987) using Beveridge-Nelson type framework concluded that the long-run impact of a 1% shock to GNP is 1.6, whereas Watson (1986) employing an unobserved components model estimated the same persistence as 0.6. Here I estimate persistence of both the permanent and the transitory components of GNP obtained by different decomposition techniques.

I use the definition of persistence of Campbell and Mankiw (1989): "continuing for a long time into the future" and use two different measures to estimate it. The first measure is proposed by Cochrane (1988) and is non-parametric in nature. It can be written as a ratio of variances or as a function of autocorrelations:

$$V^k \equiv \frac{1}{k+1}\frac{var(Y_{t+k+1}-Y_t)}{var(Y_{t+1}-Y_t)} = 1 + 2\sum\left(1-\frac{j}{k+1}\right)\rho_j \tag{24}$$

where ρ_j is the jth autocorrelation of ΔY_t. If Y_t is a random walk the above ratio is one and if Y_t is stationary it approaches to zero for large k.

The second measure is based on the assumption that ΔY_t is stationary and has a moving average representation:

$$\Delta Y_t = A(L)\varepsilon_t \tag{25}$$

where $A(L) = 1 + A_1L + A_2L^2 + A_3L^3 + \ldots$ is an infinite polynomial in lag operator and ε_t is white noise. The impact of a shock in period t on ΔY_t. in period $t+k$ is A_k, and the impact on Y_t in period $t+k$ is $\left(1+\sum_{j=1}^{k} A_j\right)$. When k approaches to infinity the sum of the moving average coefficients is $A(1)$ and it is the measure of persistence in Y_t.

Although the two measures of persistence are not exactly the same they are very close to each other. They produce the same number for a stationary series and a random walk process. As shown by Campbell and Mankiw (1989) the relation between these to measures can be stated as follows:

$$A^k(1) = \sqrt{\frac{V^k}{1-\rho_1^2}}$$

where ρ_1 is the first autocorrelation coefficient.

Table 3 reports measures of persistence of the output series and its components. The GNP series exhibits high persistence such that the degree of estimated persistence is very close to the one of a random walk process. For various permanent components of output same conclusion is reached. A 1% shock to the permanent component has a 1% effect even after 10 years. The size, however, decreases significantly when the window size is 80 quarters and ranges from 0.42% to 0.94%. The permanent components implied by both HP filters show unbelievable persistence. The effect of a 1% shock to the permanent component of HP1600 is 17 to 25 times higher than the initial level after 20 years when I use Cochrane's non-parametric or Campbell and Mankiw's parametric measures, respectively. The persistence of the permanent component of HP4 filter is much lower than HP1600 filter but still over 2.5%. As a conclusion, the shocks to the permanent components are significantly persistence within first ten years, but the size of the effect varies over longer horizons.

The finding of high persistence in output is sometimes considered to be an artifact of the failure to distinguish long-run fluctuations from short-run fluctuations. Although I find significantly high persistence in the permanent components regardless of the techniques used, I also present measures of persistence in the transitory components. There is little or no persistence in the transitory components of HP4, FD and BN procedures, independent of the measure used. When Cochrane's measure is used the transitory components obtained using SEG, HP1600 and UC show very slight persistence as opposed to the parametric measure where the degree of persistence is as high as those of the transitory components multivariate decompositions and it is around 0.4%. The transitory component of linear deterending procedure exhibits the same level of persistence as output itself. This is because the trend removes only deterministic parts but the persistence of the stochastic component of output remains as it is in the original series.

4. Conclusion

In literature, a set of summary statistics is used to characterize the behavior of long- and short-run fluctuations in output. Many facts are reported about volatility and asymmetry of output and questions such as whether shocks to output are large and infrequent and whether there is persistence and if so what is the degree of persistence are examined. All of these studies presumed that they have a clear definition of what constitutes fluctuations in the long- and short-run. These "facts" often contradicted each other and instead of answering questions, they heated existing controversies.

In this paper I compared the properties of permanent and transitory components of output obtained using seven different decomposition techniques in an attempt to test how similar or dissimilar results can be reached by using them on the same data and if there is any evidence of robustness about the pattern of long- and short-run fluctuations in output. The results show that dissimilarity is the most common outcome. Univariate and multivariate techniques yield unquestionably distinct features. Moreover there is even little agreement among the univariate decompositions themselves. I failed to reach any robust finding about the facts on output fluctuations. In the light of these results, since there is no objective criteria to enable researcher to choose the best among various decompositions, any study on macroeconomic fluctuations is suggestive and the best one can do is to hope that the technique she is using is the appropriate one for the question examined.

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Table 1: Sample Statistics of First Differences of Output and its Permanent Components

	Permanent Component		Transitory Component
	Mean (*100)	Std.Dev. (*100)	Std.Dev. (*100)
Log GNP	0.4230	1.1796	-
LIN	-	-	4.5166
SEG	-	-	2.7877
HP1600	0.3930	0.2183	2.1011
HP4	0.4240	0.7285	0.6210
FD	0.4160	1.1777	1.1760
BN	0.4170	1.3344	0.7803
UC	0.3800	0.8440	2.0393
MBN	0.3890	0.8186	3.5917
GG	0.3910	0.7563	3.0452

Table 2: Sample Statistics of Transitory Components of Output

	Permanent Component		Transitory Component		
	Skewness	Excess Kurtosis	Skewness (Steepness)	Skewness (Deepness)	Excess Kurtosis
Log GNP	-0.6579*	1.2753*	-	-	-
	(0.1927)[a]	(0.3924)			
LIN	-	-	-0.6580*	0.1032	-0.9239*
			(0.2071)	(0.1975)	(0.3957)
SEG	-	-	-0.4901*	-0.2994**	-0.2193
			(0.1820)	(0.1898)	(0.4365)
HP1600	0.2788	-0.0127	-0.5624*	-0.3898*	0.1069
	(0.2069)	(0.3729)	(0.1946)	(0.1996)	(0.3884)
HP4	-0.3860*	-0.3291	-0.3710*	-0.6088*	1.4059*
	(0.2151)	(0.4061)	(0.1984)	(0.2090)	(0.3498)
FD	-0.6440*	1.2843*	0.1687	-0.6546*	1.2943*
	(0.2038)	(0.3385)	(0.1988)	(0.1888)	(0.3934)
BN	-0.6032*	1.3532*	0.0346	-0.3461*	0.1923
	(0.2031)	(0.3747)	(0.1952)	(0.1897)	(0.3577)
UC	-0.5062*	1.4709*	-0.2694	-0.7815*	0.9672*
	(0.1965)	(0.3510)	(0.2092)	(0.2059)	(0.3865)
MBN	-0.1676	-0.1040	-0.2936	0.1237	-0.2702
	(0.2135)	(0.4253)	(0.1931)	(0.2031)	(0.3531)
GG	-0.0748	-0.0947	-0.2970	0.0058	-0.3639
	(0.2198)	(0.4046)	(0.1912)	(0.1076)	(0.3731)

[a] Standard errors are given in parantheses.
* The coefficient is different from zero at 5% significance level.
** The coefficient is different from zero at 10% significance level.

Table 3: Persistence of Log(GNP) and its Components

Gross National Product

Window(k)	V	sd(V)	A
1	1.345	0.176	1.236
2	1.589	0.255	1.343
3	1.731	0.321	1.402
4	1.799	0.373	1.429
8	1.658	0.461	1.372
16	1.115	0.426	1.125
20	1.003	0.426	1.067
24	0.956	0.443	1.042
40	0.868	0.516	0.993
80	0.922	0.769	1.023

Linear Trend

	Permanent Component			*Transitory Component*		
Window (k)	V	sd(V)	A	V	sd(V)	A
1	NA	NA	NA	1.345	0.176	1.236
2	NA	NA	NA	1.589	0.255	1.343
3	NA	NA	NA	1.731	0.321	1.402
4	NA	NA	NA	1.799	0.373	1.429
8	NA	NA	NA	1.657	0.461	1.372
16	NA	NA	NA	1.115	0.426	1.125
20	NA	NA	NA	1.003	0.426	1.067
24	NA	NA	NA	0.956	0.443	1.042
40	NA	NA	NA	0.868	0.516	0.993
80	NA	NA	NA	0.922	0.769	1.023

Segmented Trend

	Permanent Component			*Transitory Component*		
Window (k)	V	sd(V)	A	V	sd(V)	A
1	NA	NA	NA	1.263	0.166	1.164
2	NA	NA	NA	1.445	0.232	1.246
3	NA	NA	NA	1.548	0.287	1.289
4	NA	NA	NA	1.582	0.328	1.304
8	NA	NA	NA	1.370	0.381	1.213
16	NA	NA	NA	0.825	0.316	0.941
20	NA	NA	NA	0.679	0.289	0.854
24	NA	NA	NA	0.587	0.272	0.794
40	NA	NA	NA	0.203	0.121	0.467
80	NA	NA	NA	0.150	0.126	0.402

Table 3 (Continued):

Hodrick-Prescott Filter (1600)

	Permanent Component			*Transitory Component*		
Window (k)	V	sd(V)	A	V	sd(V)	A
1	1.987	0.261	8.628	1.285	0.169	1.183
2	2.956	0.475	10.525	1.464	0.235	1.262
3	3.903	0.724	12.094	1.538	0.285	1.294
4	4.822	1.000	13.443	1.539	0.319	1.294
8	8.140	2.265	17.465	1.176	0.327	1.132
16	12.710	4.861	21.824	0.490	0.187	0.730
20	14.070	5.980	22.961	0.381	0.162	0.644
24	15.011	6.961	23.717	0.347	0.161	0.615
40	17.217	10.225	25.400	0.234	0.139	0.505
80	17.642	14.726	25.712	0.162	0.135	0.419

Hodrick-Prescott Filter (4)

	Permanent Component			*Transitory Component*		
Window (k)	V	sd(V)	A	V	sd(V)	A
1	1.911	0.251	3.351	0.757	0.099	0.897
2	2.677	0.430	3.966	0.556	0.089	0.769
3	3.265	0.606	4.380	0.393	0.073	0.646
4	3.671	0.761	4.644	0.289	0.060	0.554
8	3.944	1.097	4.814	0.138	0.038	0.383
16	2.781	1.064	4.043	0.077	0.029	0.285
20	2.518	1.070	3.846	0.059	0.025	0.251
24	2.406	1.116	3.760	0.053	0.024	0.237
40	2.255	1.339	3.640	0.033	0.020	0.189
80	2.508	2.094	3.839	0.021	0.017	0.148

First Differences

	Permanent Component			*Transitory Component*		
Window(k)	V	sd(V)	A	V	sd(V)	A
1	1.345	0.176	1.236	0.620	0.081	0.851
2	1.588	0.255	1.343	0.493	0.079	0.759
3	1.727	0.320	1.401	0.403	0.075	0.686
4	1.793	0.372	1.427	0.356	0.074	0.645
8	1.650	0.459	1.369	0.196	0.055	0.479
16	1.123	0.429	1.129	0.092	0.035	0.327
20	1.015	0.431	1.073	0.075	0.032	0.296
24	0.967	0.448	1.048	0.067	0.031	0.279
40	0.878	0.521	0.998	0.041	0.024	0.218
80	0.944	0.788	1.036	0.026	0.022	0.174

Table 3 (Continued):

Beveridge-Nelson Decomposition ARIMA(3,1,3)

	Permanent Component			*Transitory Component*		
Window (k)	V	sd(V)	A	V	sd(V)	A
1	1.034	0.136	1.017	0.706	0.093	0.879
2	1.024	0.165	1.013	0.581	0.093	0.798
3	1.013	0.188	1.007	0.487	0.090	0.730
4	1.008	0.209	1.005	0.428	0.089	0.685
8	1.013	0.282	1.007	0.239	0.066	0.511
16	0.772	0.295	0.879	0.109	0.042	0.345
20	0.697	0.296	0.836	0.090	0.038	0.314
24	0.667	0.309	0.817	0.081	0.038	0.298
40	0.625	0.371	0.791	0.049	0.029	0.232
80	0.670	0.559	0.819	0.032	0.027	0.187

Unobserved Component Model

	Permanent Component			*Transitory Component*		
Window (k)	V	sd(V)	A	V	sd(V)	A
1	1.013	0.133	1.006	0.654	0.086	0.862
2	1.039	0.167	1.020	0.647	0.104	0.857
3	1.051	0.195	1.025	0.664	0.123	0.869
4	1.067	0.221	1.033	0.706	0.146	0.896
8	1.117	0.311	1.057	0.644	0.179	0.855
16	1.176	0.450	1.085	0.384	0.147	0.660
20	1.176	0.500	1.084	0.335	0.142	0.617
24	1.189	0.551	1.090	0.314	0.146	0.597
40	1.146	0.681	1.071	0.296	0.176	0.580
80	0.868	0.724	0.932	0.254	0.212	0.537

Multivariate Beveridge-Nelson Decomposition

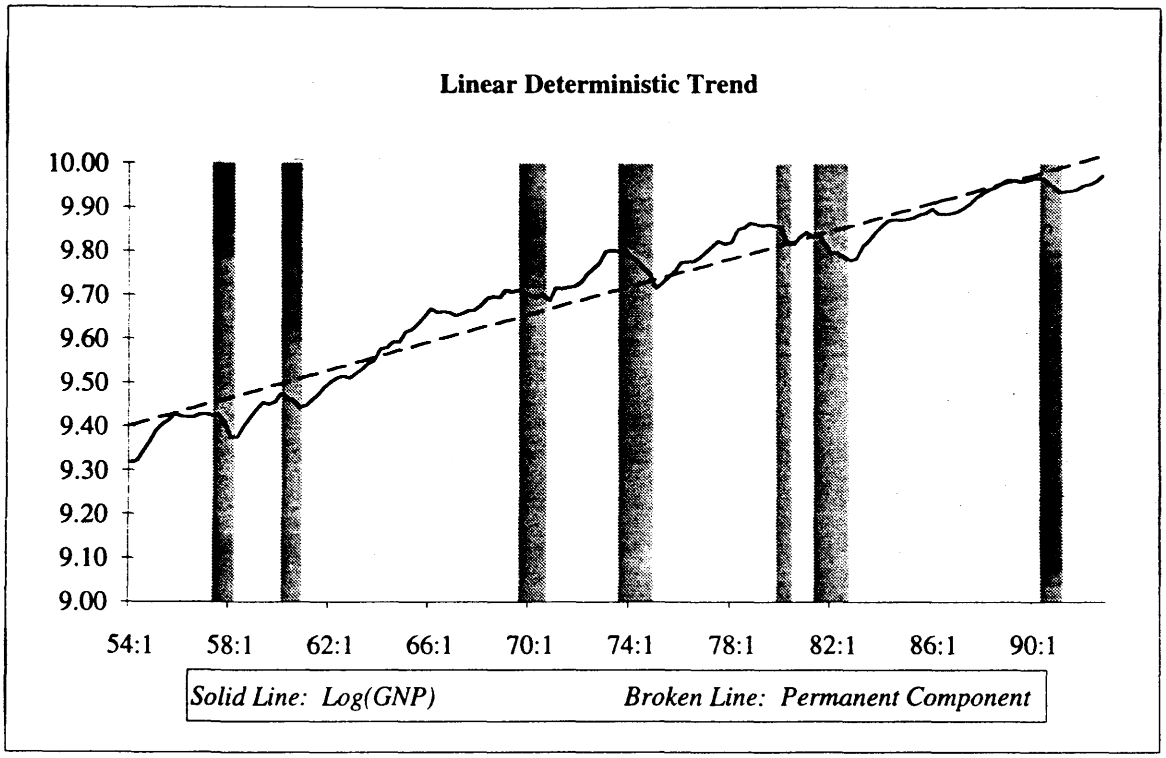
	Permanent Component			*Transitory Component*		
Window (k)	V	sd(V)	A	V	sd(V)	A
1	0.999	0.131	1.000	1.152	0.151	1.086
2	1.005	0.162	1.003	1.256	0.202	1.134
3	1.016	0.188	1.008	1.320	0.245	1.162
4	1.026	0.213	1.013	1.328	0.275	1.166
8	1.010	0.281	1.005	1.136	0.316	1.078
16	1.148	0.439	1.072	0.725	0.277	0.862
20	1.145	0.487	1.070	0.621	0.264	0.798
24	1.077	0.500	1.038	0.568	0.264	0.763
40	0.804	0.477	0.897	0.375	0.223	0.620
80	0.420	0.350	0.648	0.320	0.267	0.572

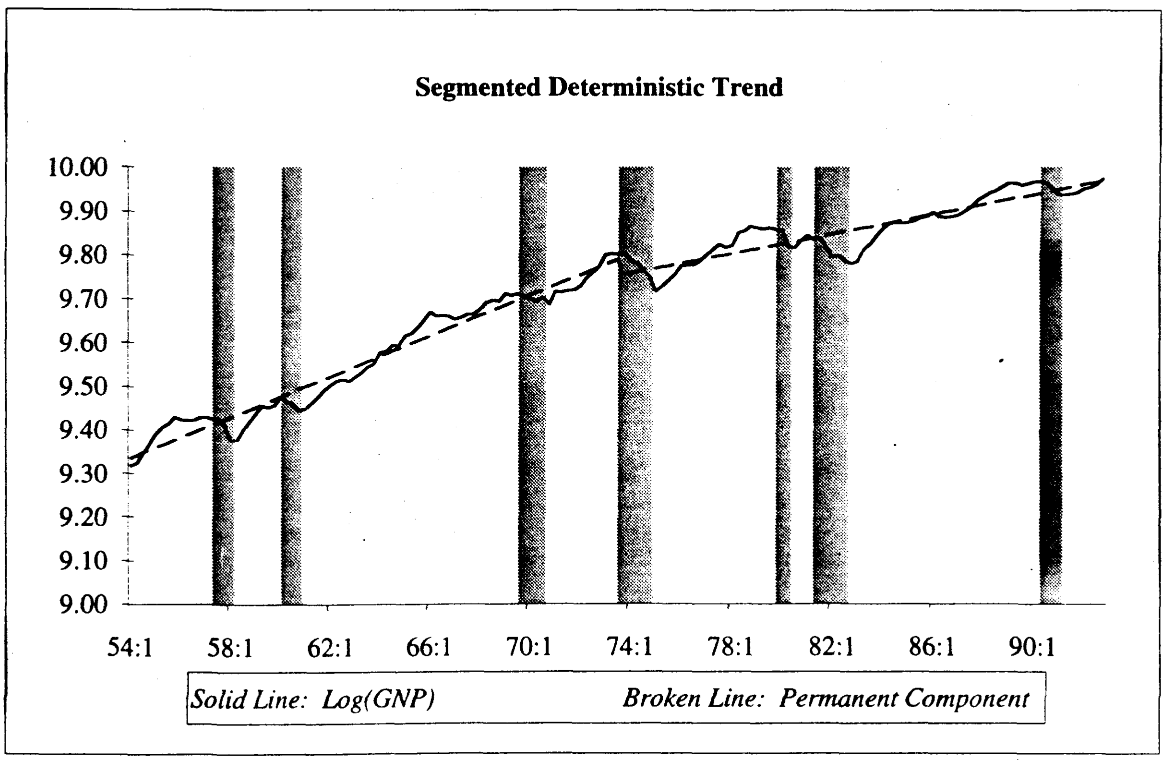
Table 3 (Continued):

Gonzalo-Granger Decomposition

Window (k)	*Permanent Component*			*Transitory Component*		
	V	sd(V)	A	V	sd(V)	A
1	0.907	0.119	0.957	1.023	0.134	1.012
2	0.923	0.148	0.965	1.032	0.166	1.016
3	1.025	0.190	1.017	1.024	0.190	1.012
4	1.088	0.226	1.048	0.986	0.205	0.993
8	1.239	0.345	1.118	0.783	0.218	0.885
16	1.359	0.520	1.171	0.507	0.194	0.712
20	1.353	0.575	1.168	0.457	0.194	0.676
24	1.273	0.590	1.133	0.431	0.200	0.657
40	0.944	0.561	0.976	0.307	0.182	0.554
80	0.581	0.485	0.766	0.260	0.217	0.510

Figure 1: Logarithm of private per capita real GNP and its Permanent Component





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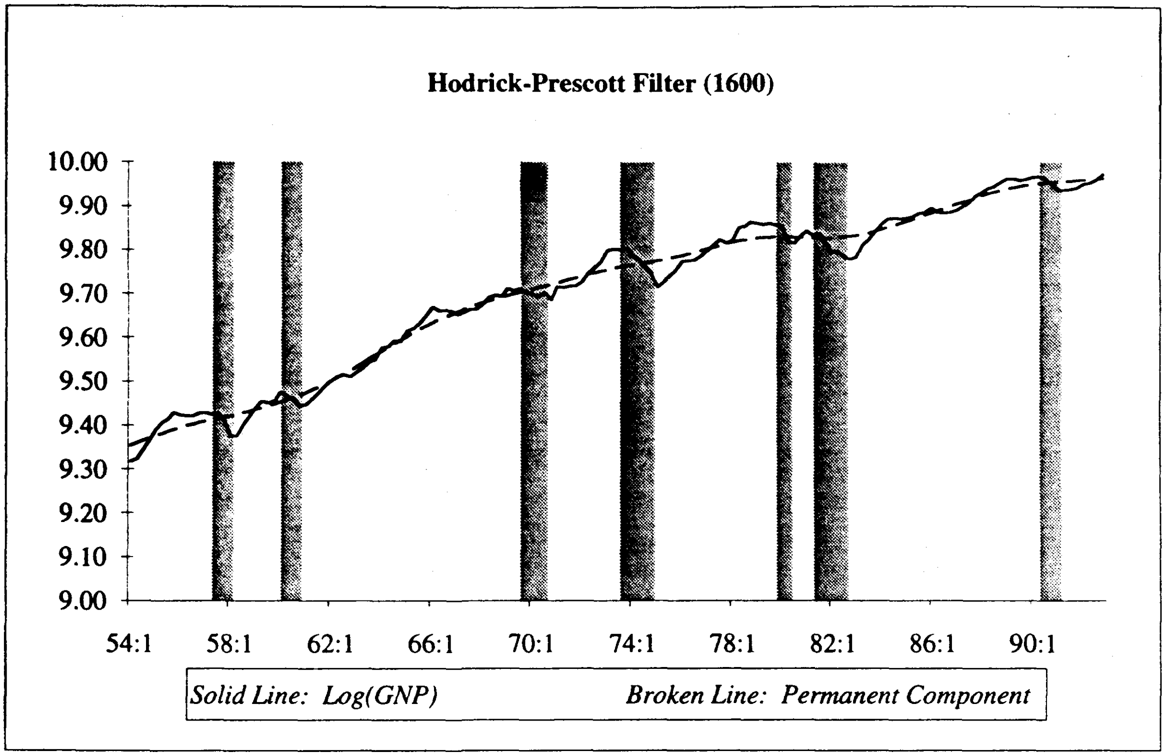

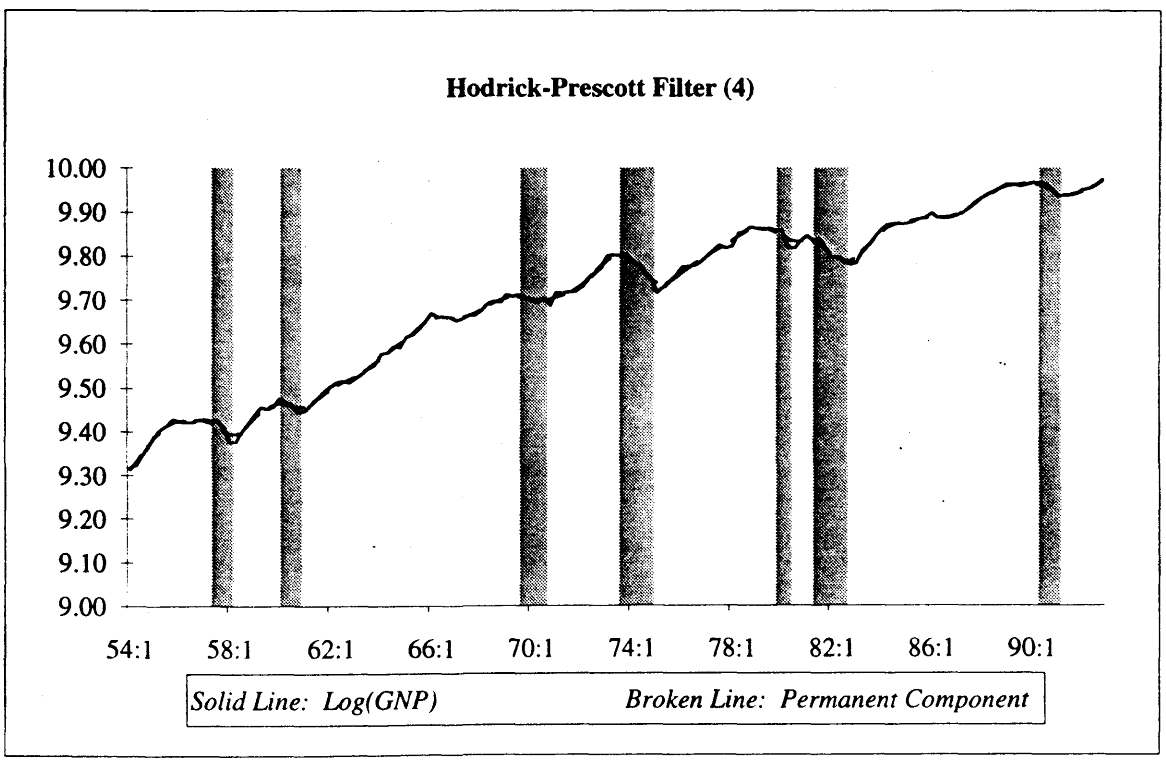

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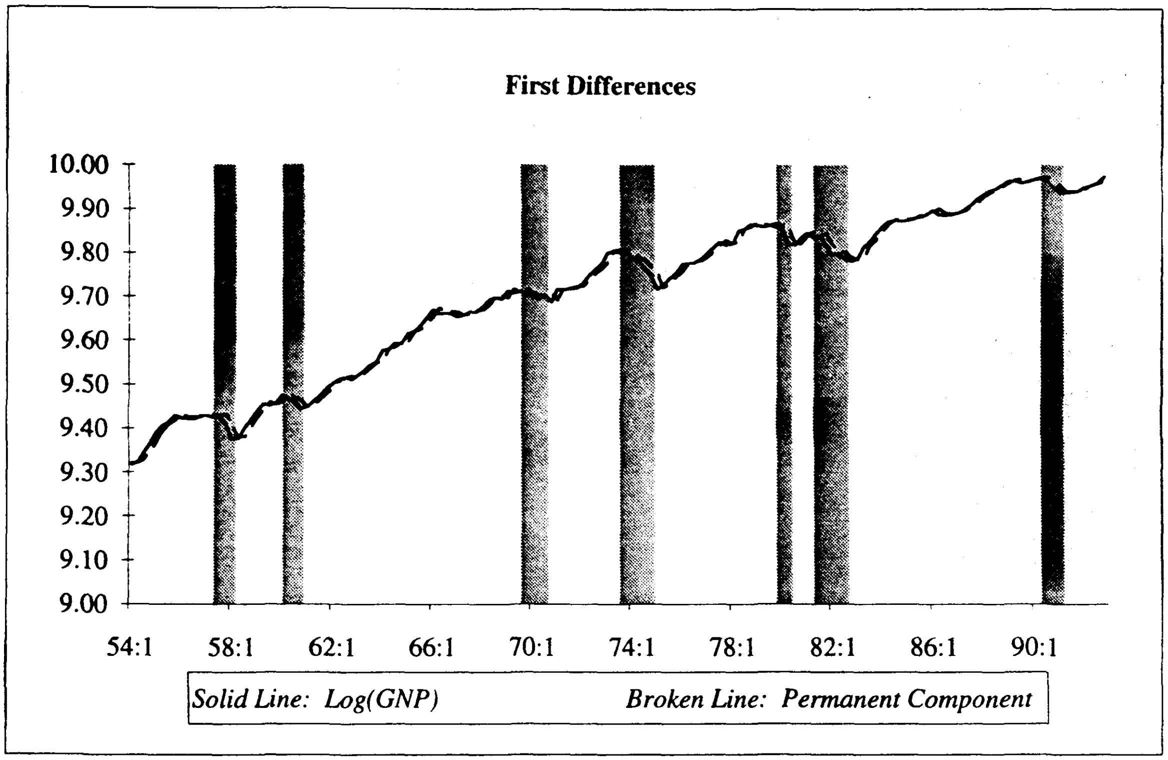

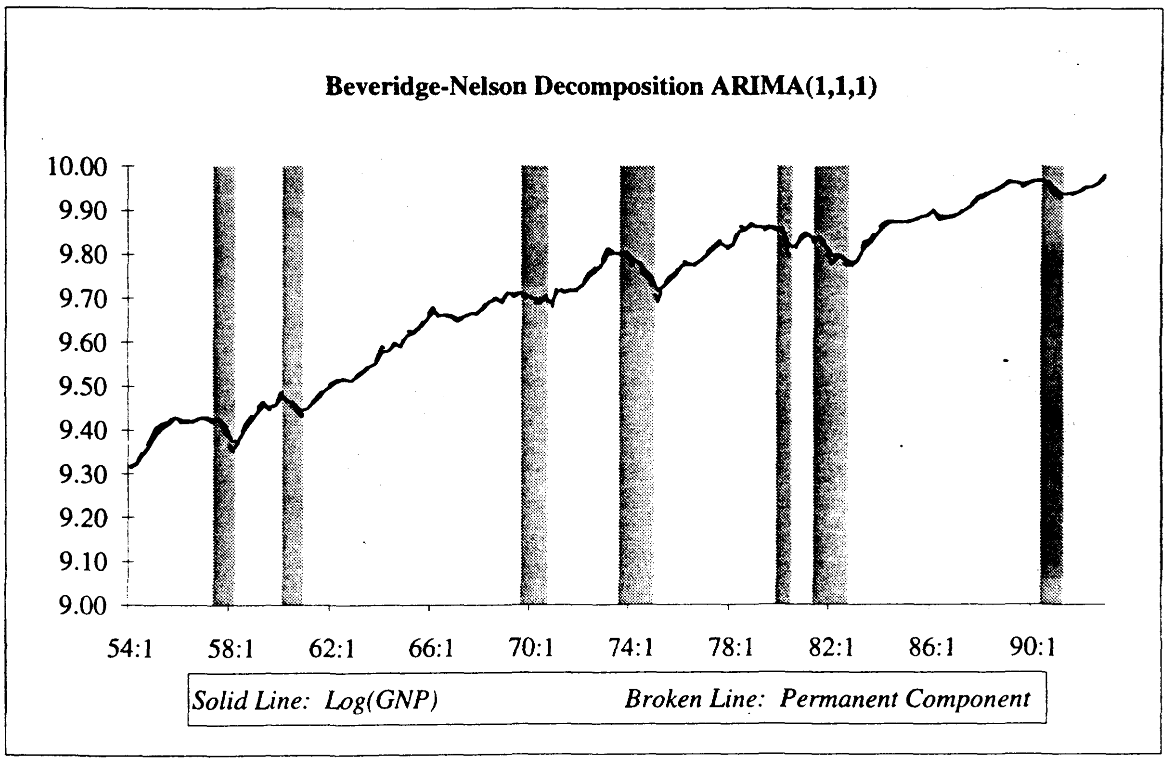

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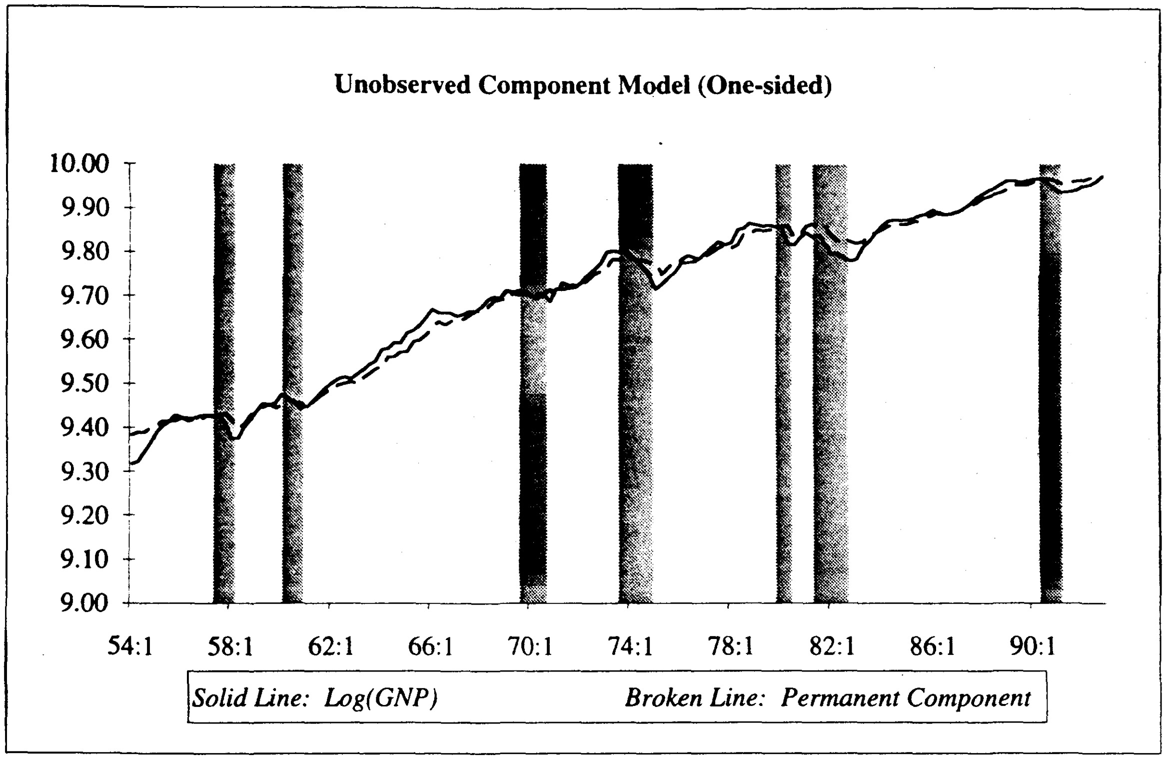

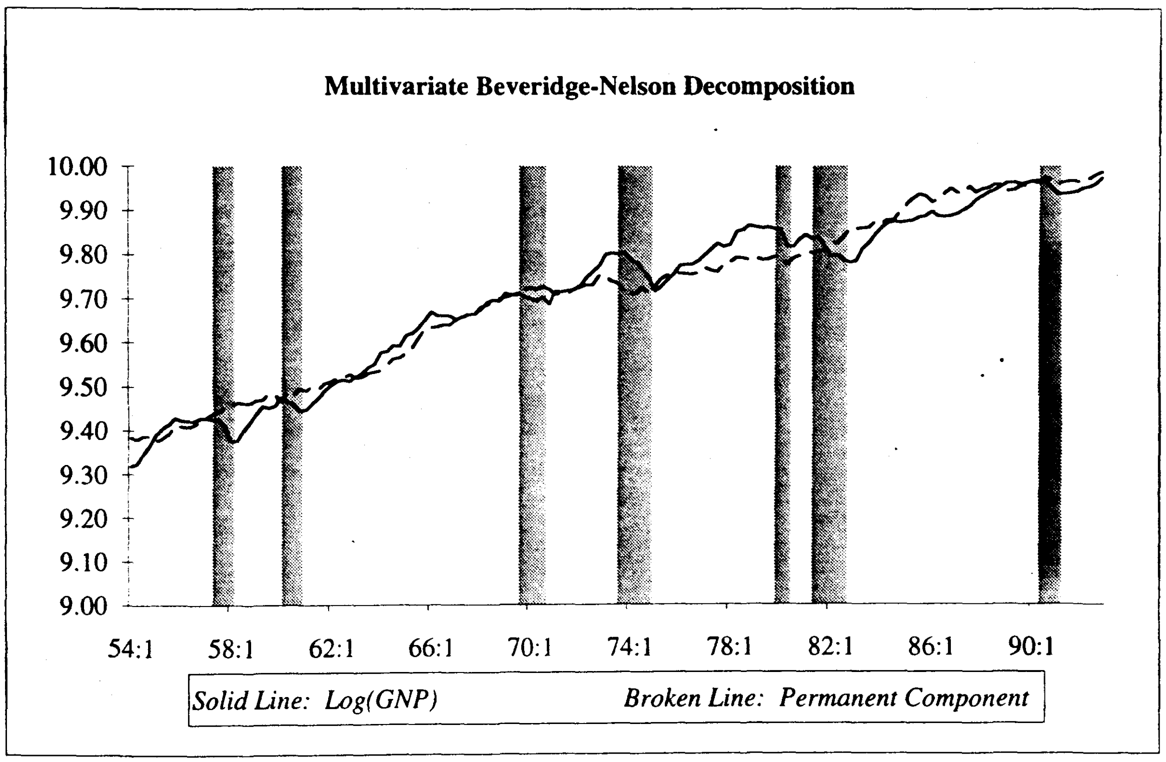

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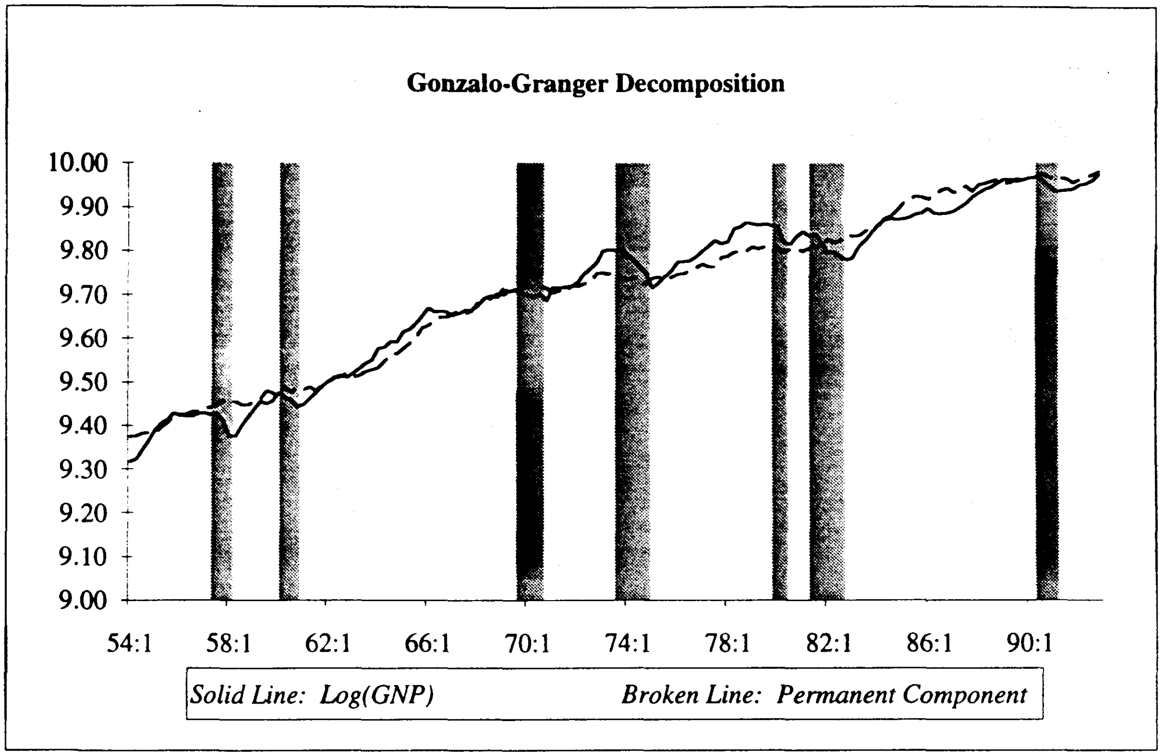
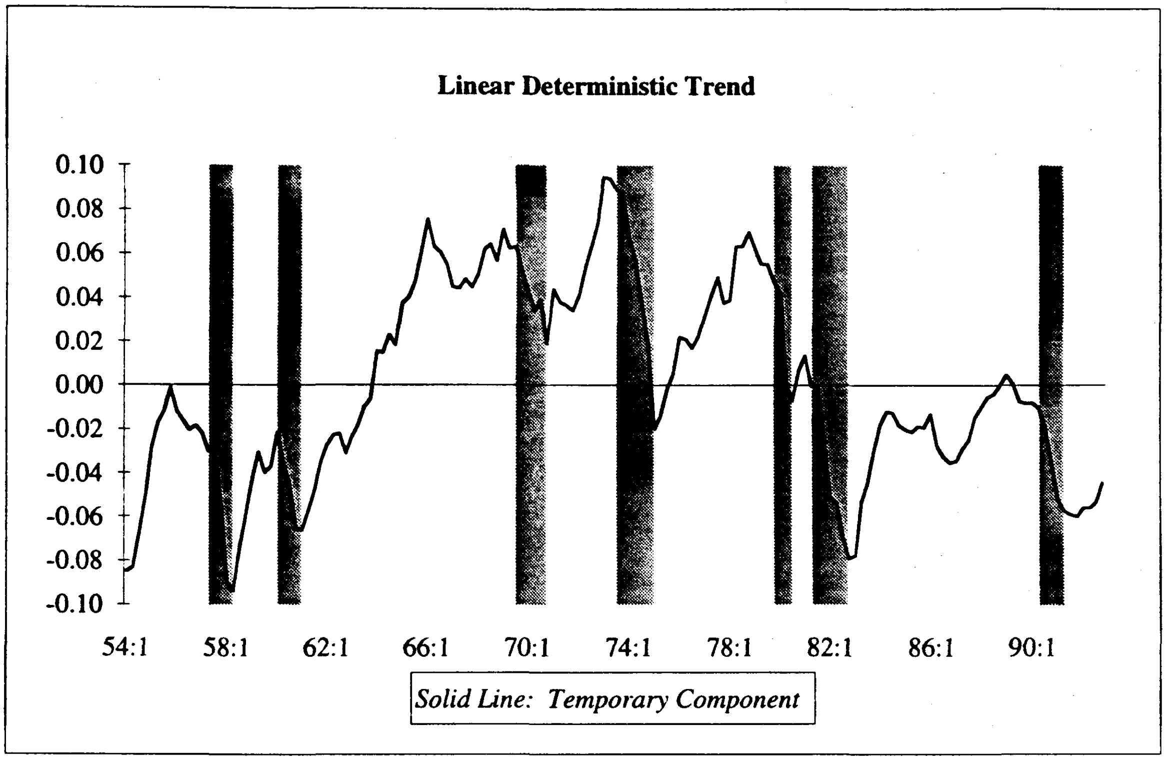
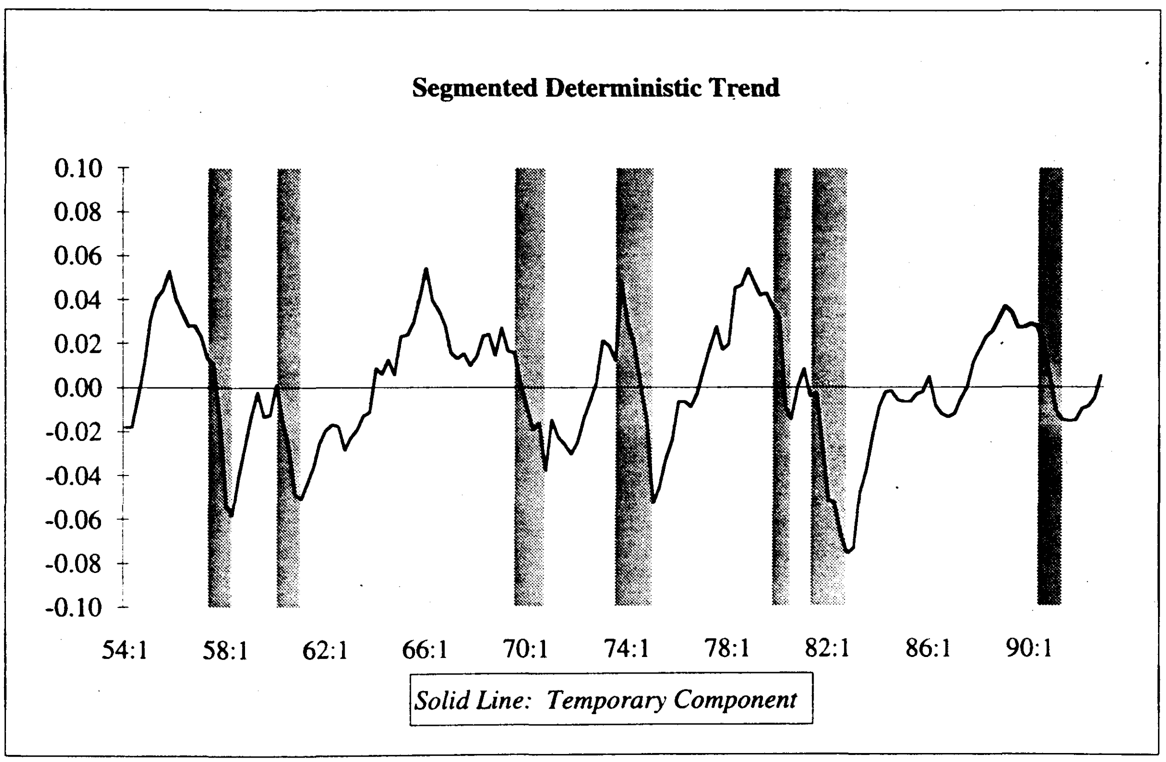


Figure 2: Transitory Components





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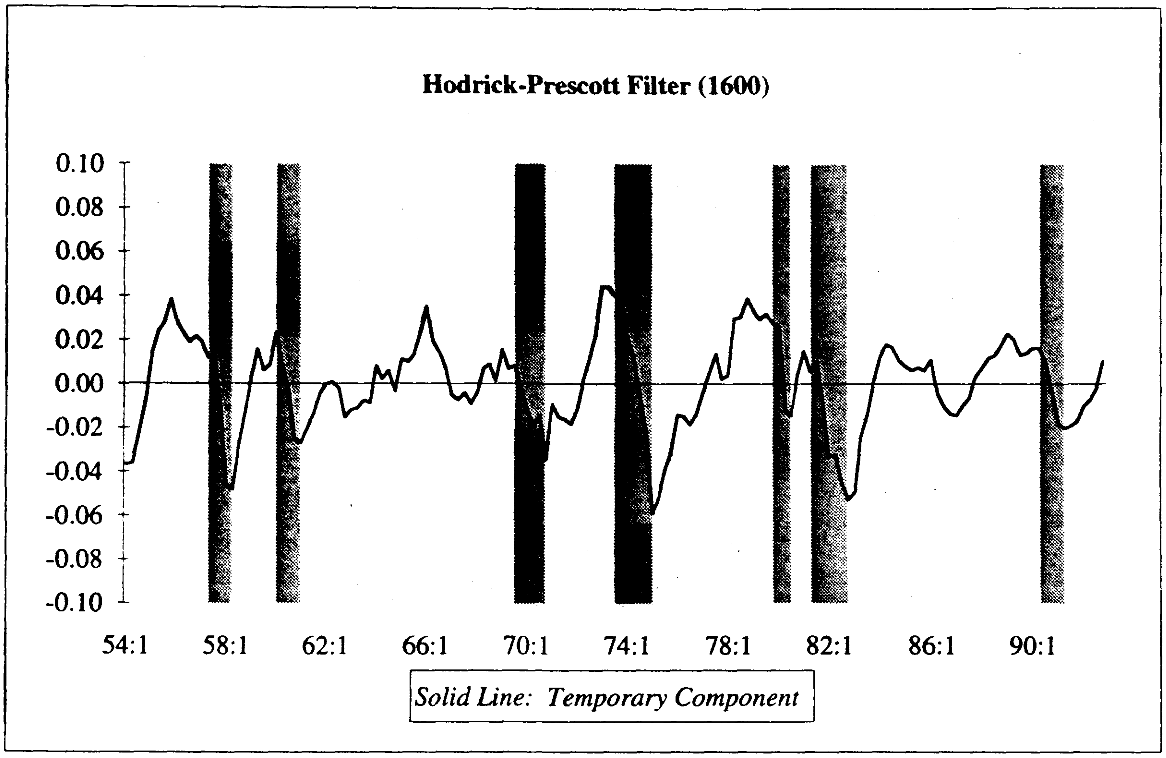

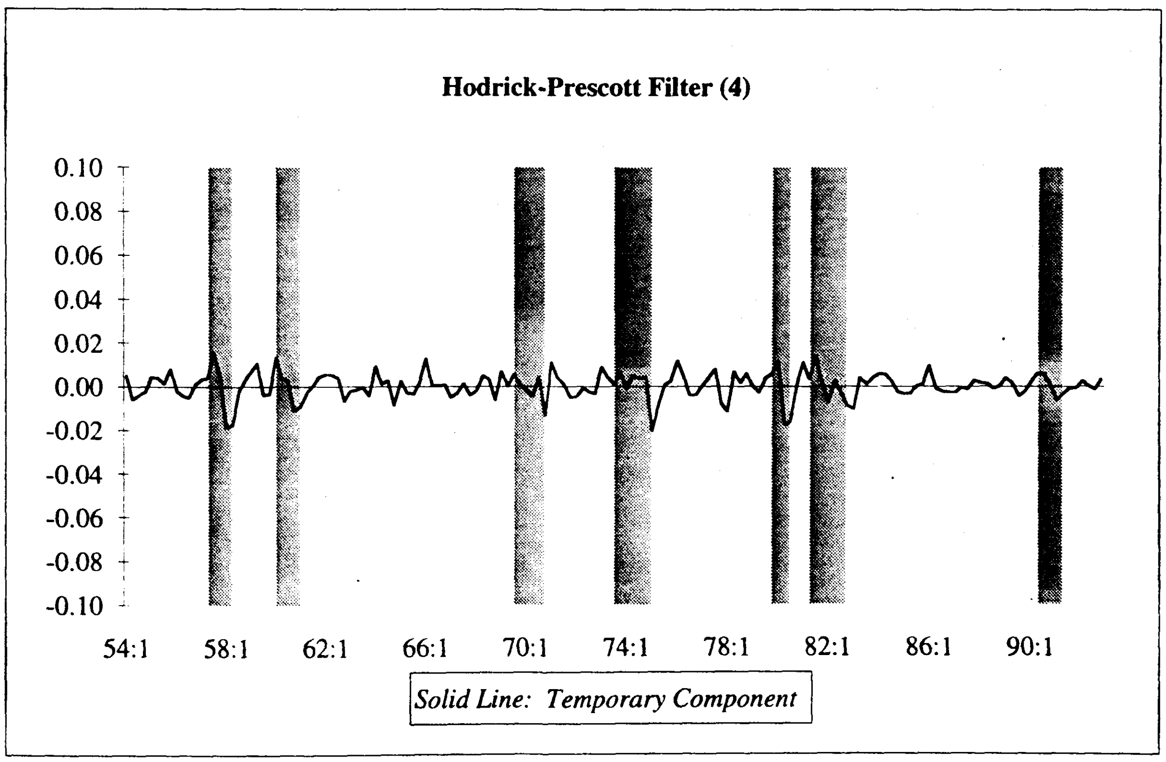

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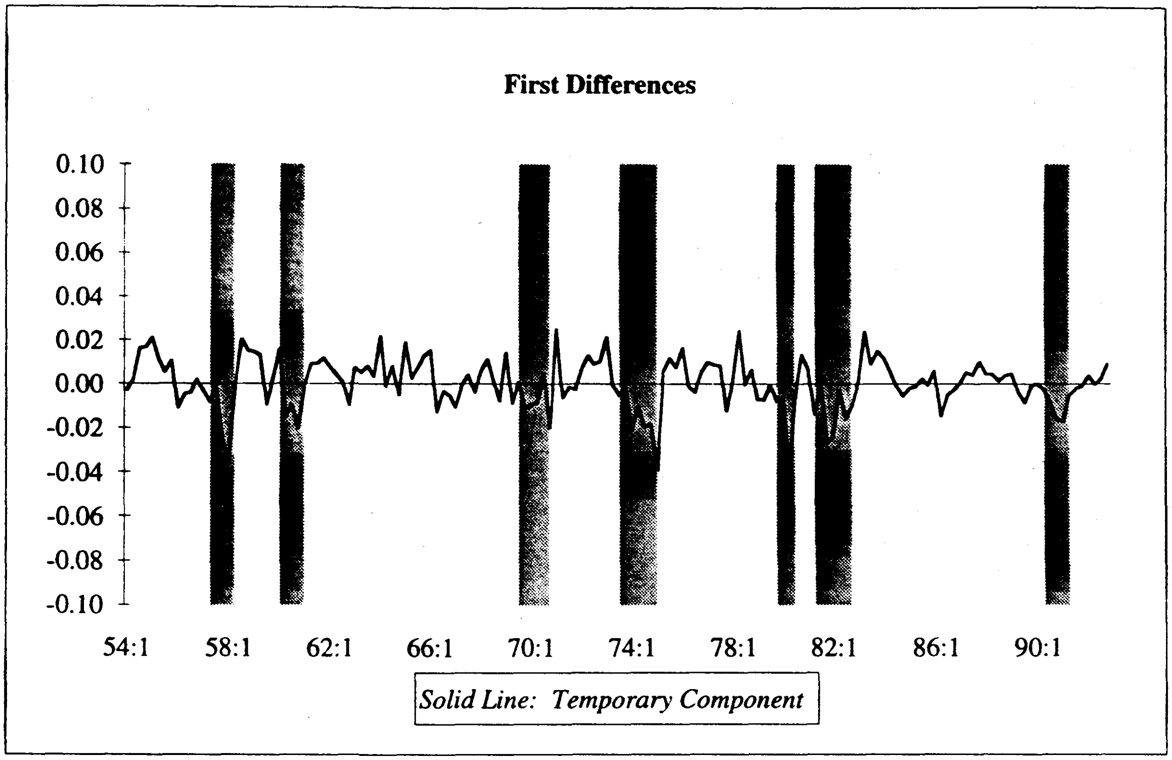

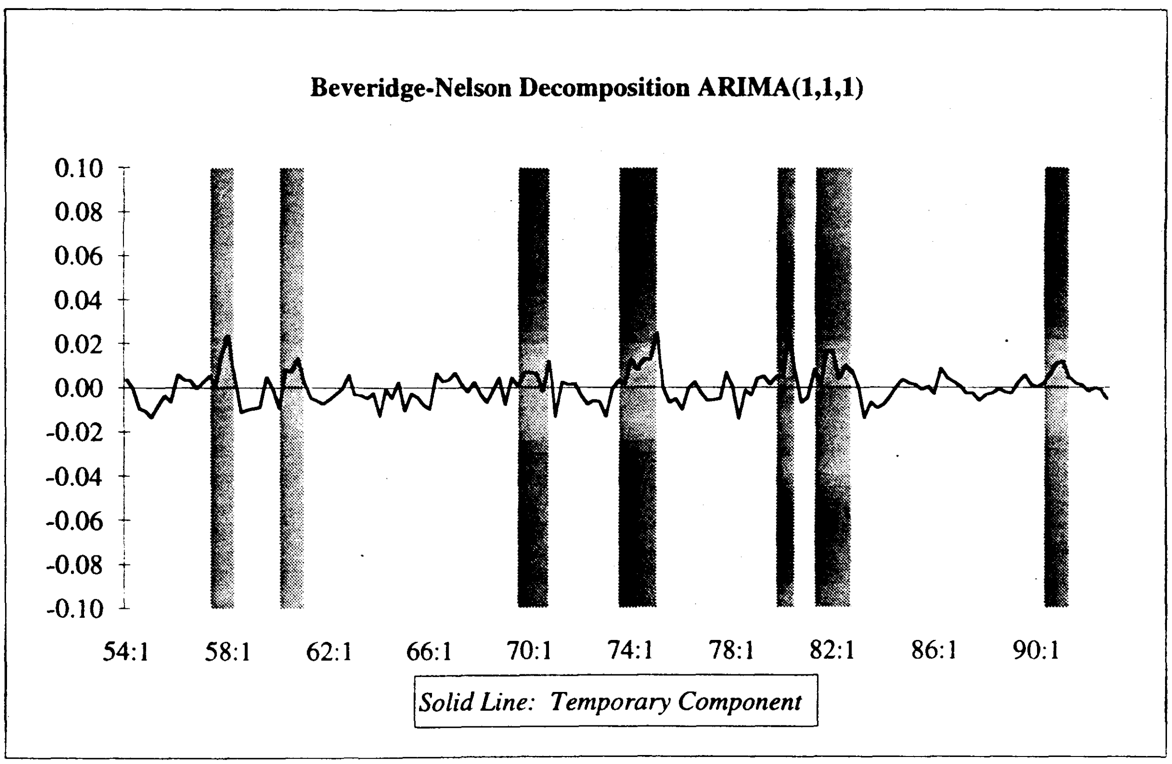

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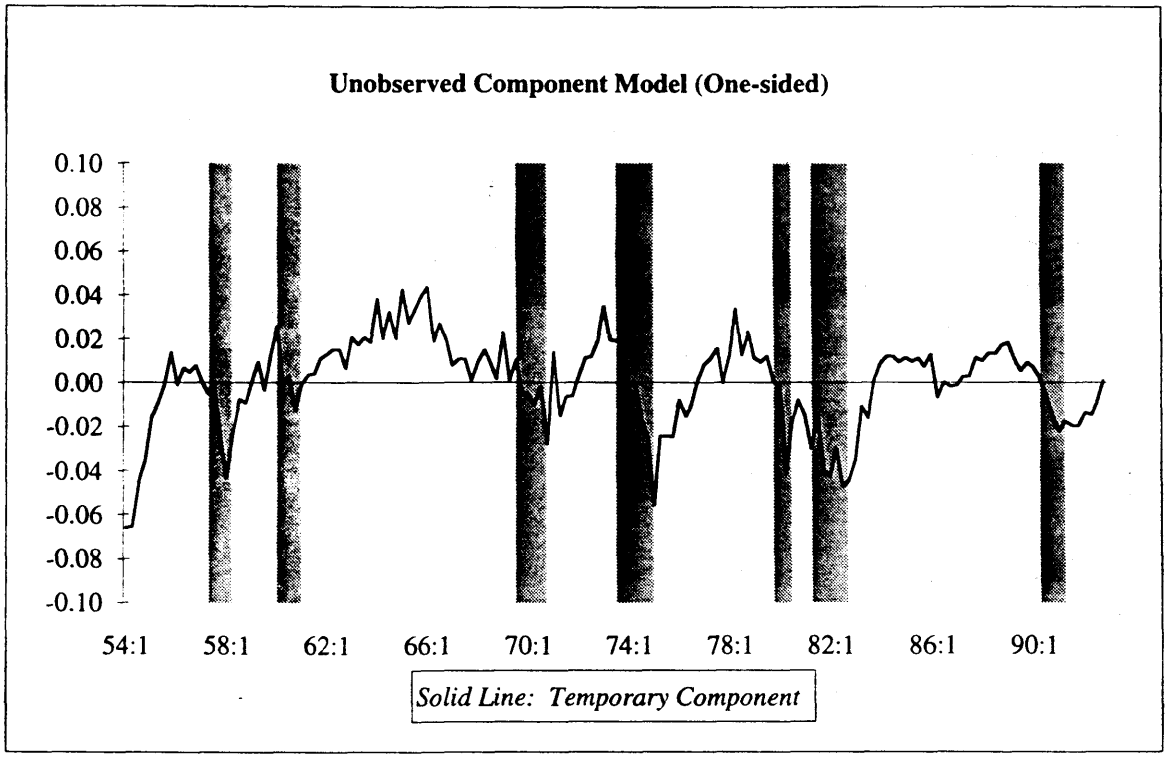

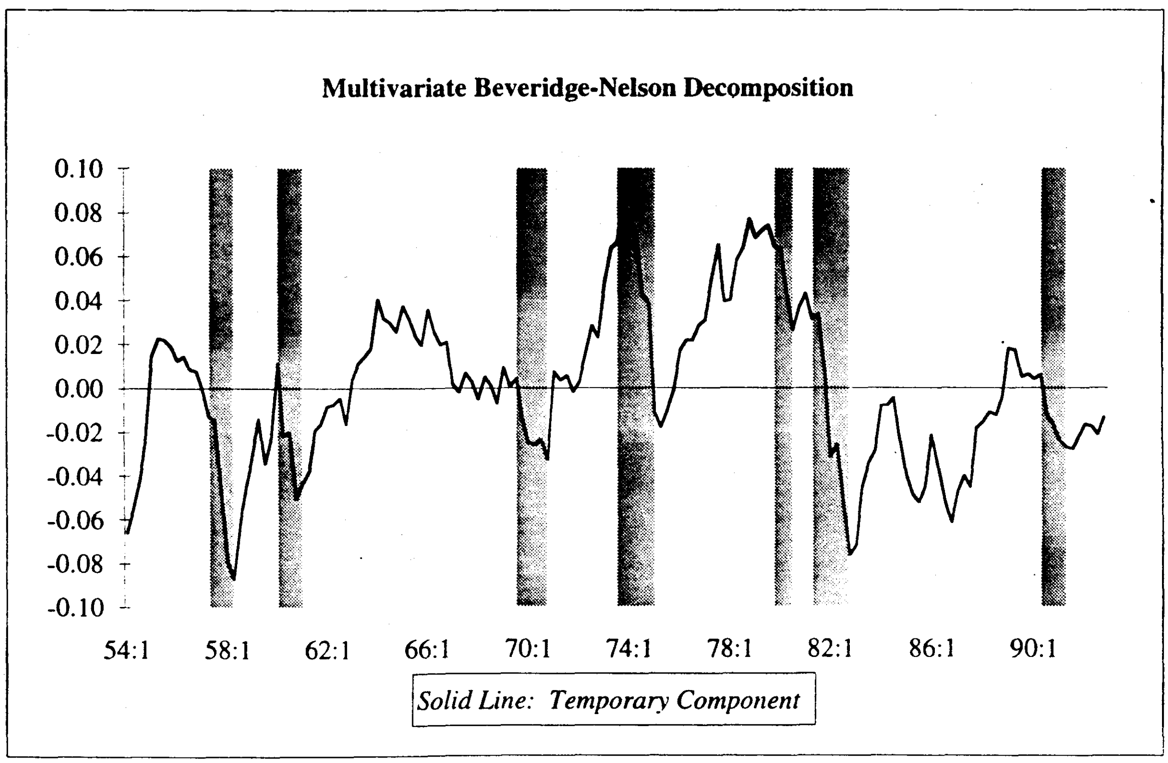

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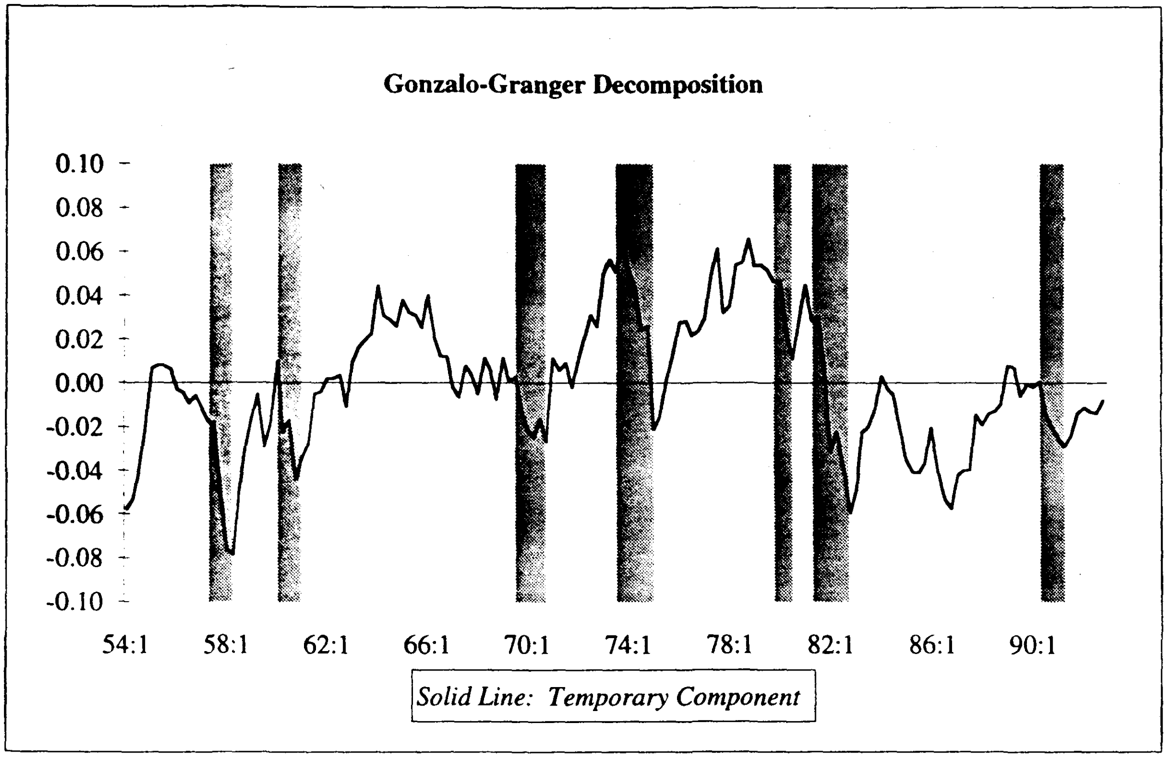

Essay 3:

The Long-run Relationship Between Saving and Investment: Stylized Fact or Fiction?

Abstract

The high correlation between domestic saving and investment rates in cross-country regressions has been interpreted by some authors as evidence that world capital markets are not integrated. Our paper reexamines the long-run saving-investment relationship across OECD countries using cointegration methods. This approach enables us to provide evidence regarding this relationship at a disaggregated level, that is, for each country separately. It also accounts for the non-stationarity of the underlying time series. In order to estimate the long-run saving-investment correlation as well as to correct for simultaneous equation bias, a non-linear single-equation error correction model is used. The results qualify the conclusions of previous studies by suggesting that saving and investment rates are not highly correlated in the long-run for most OECD countries.

1. Introduction

A positive and statistically significant correlation between saving and investment rates across countries was first documented by Feldstein and Horioka (1980). Using cross-section data for sixteen industrial countries that are members of the Organization for Economic Cooperation and Development (OECD), Feldstein and Horioka found that a sustained increase in domestic saving over a multi-year period has a roughly proportional effect on domestic investment. They interpreted this as evidence in favor of a long-run or steady-state relationship between saving and investment and concluded that this high saving-investment correlation is inconsistent with the hypothesis of world capital market integration.

The Feldstein-Horioka finding was confirmed by Feldstein (1983) for a longer time period. Subsequent research by Penati and Dooley (1984), Vos (1988), Dooley, Frankel, and Mathieson (1987), Feldstein and Bacchetta (1989), and Tesar (1991) verified the close association between domestic saving and investment both for industrial and developing countries. Although additional work by Murphy (1986), Obstfeld (1986), Finn (1990), Stockman and Tesar (1991), and Baxter and Crucini (1993), among others, has questioned the usefulness of data on saving and investment for testing hypotheses about capital mobility, the original Feldstein-Horioka finding that long-run or steady-state saving and investment rates are highly correlated across countries has not been seriously challenged.[1] As a consequence, the Feldstein-Horioka conclusion that capital markets are not highly integrated across countries has persisted in some recent work [e.g., Feldstein and Bacchetta (1989), Sinn (1992), Bayoumi and Rose (1993)].

[1] Exceptions are Murphy (1984) and Wong (1990) which question the robustness and generality of the Feldstein-Horioka conclusion. They find that the extent of correlation is sensitive to the inclusion of a small subset of countries in the sample.

The Feldstein-Horioka and subsequent studies of the long-run correlation between saving and investment, however, suffer from a number of important shortcomings. First, these studies estimate the saving-investment relationship from a cross-country regression equation, thus ignoring the time-series properties of investment and saving in each country.[2] Second, these studies do not account for the non-stationarity of the underlying time series. Both saving and investment rates in all OECD countries are integrated processes of order one. Therefore, statistical estimation and inference in such a model requires a methodology which accounts for the non-stationarity of saving and investment rates. Third, previous studies have not provided evidence concerning the long-run relationship between saving and investment at a disaggregated level, that is, for each national capital market separately.

This paper reexamines the long-run relationship between saving and investment for the group of twenty-four OECD countries. In contrast to previous studies, we employ cointegration analysis to test for the existence of a long-run saving-investment relationship. This technique utilizes all the information present in the time series of saving and investment in each country and accounts for their non-stationarity.[3] Our approach also focuses on the low-frequency properties of the data thereby eliminating the effect of cyclical variations and random shocks inherent in time-series models. If the correlation between domestic saving and investment rates is indeed a long-run phenomenon, the ratios must be cointegrated. Cointegration analysis, therefore, can provide evidence regarding the long-run relationship between saving and investment in each country separately, and,

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[2] Obstfeld (1986) calculated short-run time-series correlations between changes in saving and investment rates for nine OECD countries and concluded that the cross-section regression framework is inappropriate.

[3] Levy (1990) also makes use of cointegration analysis to investigate the long-run relationship between a number of variables including saving and investment rates. His analysis was, however, confined to the U.S. and uses a data set and time period different from ours.

consequently, incorrect generalizations of results obtained from cross-section regressions can be avoided. Contrary to earlier findings, the results of this paper support the hypothesis that saving and investment rates are not highly correlated in the long-run for most OECD countries.

The plan of the paper is as follows. The next section describes the econometric methodology used to estimate the long-run relationship between saving and investment. In section 3, the results from cointegration analysis are reported. The paper concludes in section 4 with a summary and suggestions for further work.

2. Econometric Methodology

Cointegration analysis was originally developed by Granger (1986) and Engle and Granger (1987). A brief description of the cointegration technique is provided here. Consider N non-stationary time series, $\boldsymbol{y}_t \equiv [y_{1t} \ldots y_{Nt}]$, with stationary first differences.[4] The series y_{it} are said to be integrated of order one and denoted by $y_{it} \sim I(1)$. Cointegrated series occur when a vector $\alpha = [-\alpha \;\; 1 \ldots \alpha_N]'$ exists, such that $z_t = [\mathbf{1}\, \boldsymbol{y_t}]\, \alpha$ is stationary; that is, $z_t \sim I(0)$. The constant vector α is called the cointegrating vector. Cointegration among the series is interpreted as evidence for the existence of a non-spurious long-run (steady-state) relationship among the series.

Testing for cointegration is quite simple. Cointegration requires that each component of $\boldsymbol{y}_t$ be I(1). This condition can be tested for using the Augmented Dickey-

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[4] In our case, N equals two and the series are the domestic saving and investment rates in each country.

Fuller statistic (ADF) (Dickey and Fuller (1979, 1981), and Fuller (1976)). If the components of y_t are I(1), then the cointegrating regression

$$y_{1t} = \alpha_1 + \sum_{j=2}^{N} \alpha_j y_{jt} + u_t \tag{2}$$

is estimated to obtain a vector of coefficients $\alpha = [-\alpha \quad 1 \; ... \; \alpha_N]$. The series

$$z_t = [1 \; y_t]\,\hat{\alpha} = y_{1t} - \hat{\alpha}_1 - \hat{\alpha}_2 y_{2t} - \ldots - \hat{\alpha}_N y_{Nt}$$

is formed and subjected to a procedure essentially the same (except for the distribution of the test statistic) as the ADF test to see if it is I(1). The null hypothesis of non-cointegration of y_t corresponds to the null hypothesis that z_t is I(1). If one rejects the null, one concludes that $y_1,...,y_N$ are cointegrated.

Should the non-stationary series y_t be found to be cointegrated, the next step is estimation and inference concerning long-run equilibria. Banerjee, Dolado, Hendry, and Smith (1986), Phillips (1986) and Phillips and Durlauf (1986) have shown that conventional tests in multivariate regressions with integrated processes cannot be applied asymptotically. In this case, classical asymptotic theory breaks down and the presence of nuisance parameter dependencies in the limiting distribution theory raises new issues. Statistical estimation and inference in these models requires a methodology which accounts for the non-stationarity of the underlying time series.

To illustrate these points, we follow the exposition by Phillips and Loretan (1991). Consider the vector y_t of N I(1) processes, and let u_t be an N-vector of strictly stationary and ergodic time series with mean zero and finite covariance matrix $\Omega > 0$. We further partition these vectors as follows

$$\boldsymbol{y}_t = \begin{bmatrix} y_{1t} \\ \boldsymbol{y}_{2t} \end{bmatrix}_{m}^{1},$$

$$\boldsymbol{u}_t = \begin{bmatrix} u_{1t} \\ \boldsymbol{u}_{2t} \end{bmatrix}_{m}^{1}, \quad \mathrm{N = m + 1}$$

and assume that the generating mechanism for $\mathbf{y}_t$ is the cointegrated system

$$y_{1t} = \boldsymbol{a}\boldsymbol{y}_{2t} + u_{1t} \tag{3}$$

$$\Delta \boldsymbol{y}_{2t} = \boldsymbol{u}_{2t} \tag{4}$$

where Δ is the first-difference operator.

Phillips and Durlauf (1986) show that under appropriate centering and scaling, least squares estimation of the cointegrating vector $\boldsymbol{a}$ in (3) produces coefficient estimates which are asymptotically non-normal. Also, OLS leads "... in general to estimators that are asymptotically biased, and whose distributions involve unit root asymptotics and non-trivial nuisance parameters" (Phillips and Loretan (1991), p. 426). Phillips (1986), Phillips and Durlauf (1986), and Phillips and Loretan (1991) have demonstrated that standard tests, such as the Wald test, no longer yield asymptotically distributed chi-squared statistics.

To produce asymptotically efficient estimates of the long-run multiplier vector $\boldsymbol{a}$ in the presence of contemporaneous correlation of u_{1t} and $\boldsymbol{u}_{2t}$ (long-term endogeneity of $\boldsymbol{y}_{2t}$), Phillips and Loretan (1991) proposed the following single-equation error correction (SEECM) model:

$$y_{1t} = \boldsymbol{a}\boldsymbol{y}_{2t} + d_1(L)(y_{1t} - \boldsymbol{a}\boldsymbol{y}_{2t}) + d_2(L)\Delta\boldsymbol{y}_{2t} + d_3(L^{-1})\Delta\boldsymbol{y}_{2t} + v_t \tag{5}$$

where $d_1(L) = \sum_{j=1}^{\infty} d_{1j}L^j$, $d_2(L) = \sum_{j=0}^{\infty} d_{2j}L^j$, and $d_3(L^{-1}) = \sum_{k=1}^{\infty} d_{3k}L^{-k}$. Phillips and Loretan (1991) include leads of y_{2t} in order to deal with the presence of simultaneous equation bias. The above specification will be referred to as the PL-SEECM model. Estimation of a in (5) is achieved through a simple non-linear least-squares (NLLS) regression. The NLLS estimate of a from (5) is fully efficient in the limit, asymptotically median unbiased, and asymptotically equivalent to the full-system maximum liklihood and spectral regression estimators. Conventional chi-squared criteria for inferential purposes with respect to all coefficients in (5) can be employed.

3. Empirical Estimates

Data and Unit Root Tests

The data used are annual observations for the twenty-four OECD countries obtained from the National Accounts of the OECD Countries, 1960-1988, Volume I. Saving and investment rates are defined as ratios of gross domestic saving (S) and gross domestic investment (I) to gross domestic product (GDP), respectively.

Cointegration requires that both I/GDP and S/GDP be I(1) for each country in our sample. Table 1 reports the results of ADF tests for the stationarity of domestic saving and investment rates for each country over the 1960-1988 time period.[5] The null hypothesis of a unit root can not be rejected even at the ten percent level for all series. The evidence

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[5] We do not use the critical values from the Dickey and Fuller (1976) tables since they are sensitive to nuisance parameters due to the small sample size. Instead we derive our own critical values at different levels of statistical significance from Monte Carlo simulations with 50,000 replications and 29 observations.

strongly suggests that each series is characterized as integrated of order one and we can, therefore, proceed to cointegration tests.[6]

Cointegration Test Results

Table 2 reports the results from the estimation of cointegrating regressions by ordinary least squares for each country. The null hypothesis of perfect capital mobility is that the residuals from the cointegrating regression for a country are I(1), or, equivalently, that gross domestic saving and investment rates for the country in question are not cointegrated. The ADF test is applied to the residuals from the cointegrating regressions to test whether they are I(1). As Table 2 indicates, domestic saving and investment rates appear to be cointegrated for Australia, Denmark, Finland, Luxembourg, Canada, France, Greece, Iceland, Sweden, and the U.S. at the five percent level. For the remaining fourteen countries, we are unable to reject the null hypothesis of non-cointegration at the five percent level.[7]

Contrary to the findings of the Feldstein-Horioka and other studies which use the cross-country regression approach, our cointegration analysis provides evidence in support of the hypothesis that saving and investment rates are not correlated in the long run for fourteen of the twenty-four OECD countries. Consistent with the findings by Obstfeld (1986), our results indicate that pooling the time-series observations across countries is inappropriate. It remains, however, to explain why saving and investment rates for ten of

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[6] We also applied the ADF test to the differenced saving and investment ratios and rejected the null hypothesis of non-stationarity at the five percent level for all series.

[7] Although the point estimates of the coefficient on the saving rate, reported in Table 2, are large for many of the fourteen countries for which we are unable to reject non-cointegration, these estimates are meaningless since our inability to reject the hypothesis of non-cointegration indicates the absence of a long-run relationship between saving and investment rates for these countries. In technical terms, the regression relationship is spurious since the two variables are integrated of order one and are not cointegrated, violating the assumptions needed for a well-defined estimator.

the countries, including the U.S. and Canada, are correlated in the long run.[8] We turn now to examine the extent of this long-run correlation.

Estimation of the Long-Run Saving-Investment Relationship

We move next to determine the extent of long-run correlation between saving and investment for the ten countries for which the null hypothesis of non-cointegration was rejected at the five percent level. Table 3 reports the estimates of the PL-SEECM models for these ten countries. To estimate equation (5), the orders of $d_1(L)$, $d_2(L)$, and $d_3(L^{-1})$ must be truncated. To select the best model for equation (5), we start with a very general model (four lags for error correction terms and saving ratios, and four leads for saving ratios) and test sequentially whether restricted versions are consistent with the data. The selection of the final models was based on the magnitude of the estimated residual variance and their performance with respect to two serial correlation tests (Durbin-Watson test and Box-Pierce Q test).

Looking at the cointegrating factors in Table 3, we first observe that the estimated long-run saving-investment relationship for Luxembourg is, contrary to economic reasoning, negative. We think that special factors may account for this inverse relationship (small country with a big banking sector). Since this result is not amenable to an intuitive interpretation, we subsequently exclude Luxembourg when commenting on the NLLS estimates of the saving-investment correlation. For the remaining nine countries the long-run saving coefficient estimate is large for all of them but Australia (0.386) and the U.S.

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[8] We examined whether size, openness, and interaction of size and openness could explain the varying degrees of capital mobility across countries. More specifically, we classified countries as large or small, and/or open or closed and examined the relationship of these classifications to the obtained evidence for cointegration. The evidence, however, was inconclusive.

(0.304)[9]. For the rest of the countries the coefficient estimate ranges from 0.741 in Sweden to 1.040 in Iceland. The interpretation for the cointegrating factor is, say, for the U.S. that a one-dollar increase in domestic saving leads to an increase in domestic investment by only thirty cents in the long-run. The hypothesis of perfect correlation (β=1) cannot be rejected for Canada, Finland, France, Greece and Iceland at the five percent level of statistical significance. For Australia, Denmark, Sweden and the U.S., however, we can reject the hypothesis of β=1, thereby indicating that saving and investment rates are only imperfectly related in the long run.

According to the above results, the Feldstein-Horioka finding is supported for only five out of twenty-four OECD countries. Our investigation of the long-run relationship between saving and investment using cointegration analysis thus reveals new insights suggesting that for most OECD countries the high correlation found using cross-country regressions is not robust to a more suitable econometric methodology.

4. Conclusions

This paper employed cointegration methods, which analyze the low frequency properties of the data to provide evidence regarding the long-run relationship between saving and investment at a disaggregated level, that is, for each of twenty four OECD countries separately. Our results demonstrate that saving and investment rates are not correlated in the long run for fourteen countries and are only imperfectly correlated for another five. Accordingly, inferences about the degree of capital mobility based on the

9 For Australia, the estimated coefficient is not statistically different from zero. A number of alternative specifications were estimated for Australia. None of them, however, produced satisfactory results in terms of statistical significance for the coefficients of the error correction terms. The estimate of the saving retention coefficient was, however, stable across different specifications.

methodology of Feldstein and Horioka (1980) are suspect not only on theoretical grounds that several authors have emphasized (and with which we agree), but also on the empirical grounds that saving and investment rates are actually not very closely related at all in the long-run.

Future research should be directed toward applying the techniques used here to data for developing countries so as to determine the generality of our findings. It would also be useful to develop structural models of the long-run determinants of saving and investment to assess why a small number of OECD countries exhibit a high long-run correlation between saving and investment, while the majority of countries do not.

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Table 1 : Augmented Dickey-Fuller Unit Root Test Results (1960-1988)

Country	ADF Test Statistics for Saving Ratio (S/GDP)	Number of lags used	ADF Test Statistics for Gross Investment Ratio (I/GDP)	Number of lags used
Australia	-0.266	[0]	0.087	[1]
Austria	-0.652	[4]	-0.440	[0]
Belgium	-0.213	[0]	-0.420	[0]
Canada	0.022	[0]	-0.331	[0]
Denmark	-1.237	[2]	-1.032	[0]
Finland	-0.579	[0]	-0.547	[2]
France	-1.086	[0]	-0.502	[0]
Germany	-0.818	[0]	-1.246	[2]
Greece	-0.259	[0]	-0.285	[0]
Iceland	-0.797	[0]	-0.772	[0]
Ireland	-0.106	[0]	-0.276	[0]
Italy	-1.638	[0]	-0.941	[0]
Japan	-0.053	[0]	-0.655	[4]
Luxembourg	0.837	[0]	-0.819	[4]
Netherlands	-1.143	[0]	-1.010	[0]
New Zealand	-0.358	[0]	-0.544	[0]
Norway	-0.495	[0]	-0.353	[0]
Portugal	-0.187	[4]	0.118	[2]
Spain	-0.424	[0]	0.247	[0]
Sweden	-1.117	[0]	-1.188	[2]
Switzerland	0.417	[0]	-0.273	[0]
Turkey	0.942	[0]	0.415	[0]
United Kingdom	-0.446	[0]	0.006	[0]
United States	-0.857	[0]	-0.250	[4]

1. For each of the series, y_t, the following ADF regression is run:

$$\Delta y_t = \gamma y_{t-i} + \sum_{i=1}^{4} \phi_i \Delta y_{t-i} + \varepsilon_t$$

where Δ is the first-difference operator and ε_t is a stationary random error. Lags were retained in the regression based on their statistical significance. The null hypothesis of non-stationarity is rejected when γ is significantly negative.

2. The ADF critical values, provided below, are derived from Monte Carlo simulations with 50,000 replications and 29 observations.

Level	0 lags	1 lag	2 lags	3 lags	4 lags
1%	-2.813	-3.611	-3.628	-3.677	-3.686
5%	-2.032	-2.788	-2.809	-2.817	-2.817
10%	-1.646	-2.364	-2.383	-2.383	-2.387

Table 2 : Cointegrating Regressions with ADF Test Statistics (1960-1988)

Country	Constant	S/GDP	adj R^2	ADF Test Stat.	No. of lags
Australia	0.170	0.374	0.323	-4.676[a]	[0]
Austria	0.030	0.900	0.779	-3.318[c]	[0]
Belgium	0.076	0.646	0.453	-3.250[c]	[0]
Canada	0.048	0.854	0.645	-3.854[b]	[0]
Denmark	0.064	0.810	0.900	-5.414[a]	[0]
Finland	0.010	1.024	0.577	-4.401[a]	[1]
France	0.036	0.837	0.900	-4.253[b]	[0]
Germany	-0.009	0.994	0.755	-2.281	[4]
Greece	0.070	0.809	0.878	-3.721[b]	[0]
Iceland	0.115	0.624	0.282	-3.758[b]	[0]
Ireland	0.142	0.482	0.030	-1.764	[0]
Italy	0.059	0.750	0.570	-3.123	[0]
Japan	-0.001	0.981	0.768	-1.720	[2]
Luxembourg	0.295	-0.098	0.075	-4.978[a]	[2]
Netherlands	-0.018	1.020	0.704	-2.145	[0]
New Zealand	0.185	0.302	0.003	-3.390[c]	[2]
Norway	0.434	-0.527	0.082	-2.602	[0]
Portugal	0.233	0.141	0.025	-3.092	[1]
Spain	0.047	0.813	0.541	-3.511[c]	[1]
Sweden	0.052	0.783	0.877	-4.020[b]	[0]
Switzerland	-0.127	1.350	0.486	-1.417	[0]
Turkey	0.028	0.955	0.732	-2.400	[0]
United Kingdom	0.153	0.188	0.025	-2.411	[0]
United States	0.108	0.429	0.499	-3.829[b]	[3]

1. For each country, the following cointegrating regression is run:

$$(I/GDP)_t = a + b(S/GDP)_t + \mu_t$$

where μ_t is the disturbance term.
Standard errors for the parameters in the cointegrating regressions are not reported since they are not consistently estimated.

2. See Table 1 for description of the ADF test. In this case, the series in question is the error term from each cointegrating regression, that is, μ_t. The critical values derived from Monte Carlo simulations with 50,000 replications and 29 observations are:

Level	0 Lags	1 Lag	2 Lags	3 Lags	4 Lags
1%	-4.3202	-4.3081	-4.1365	-4.0835	-3.9007
5%	-3.5650	-3.5650	-3.3930	-3.3313	-3.1882
10%	-3.1977	-3.1971	-3.0438	-2.9898	-2.8504

[a] Significant at the 1 % level. [b] Significant at the 5 % level. [c] Significant at the 10 % level.

Table 3 : Estimation of the Long-run Equilibrium between Investment and Saving Ratios in OECD Countries Using Phillips-Loretan Non-Linear Single Equation Error Correction Model (PL-SEECM) (1960-1988)

$$\left(\frac{I}{Y}\right)_t = \alpha + \beta\left(\frac{S}{Y}\right)_t + d_1(L)\left(\left(\frac{I}{Y}\right)_t - \alpha - \beta\left(\frac{S}{Y}\right)_t\right) + d_2(L)\Delta\left(\frac{S}{Y}\right)_t + d_3(L^{-1})\Delta\left(\frac{S}{Y}\right)_t + v_t$$

where $d_1(L) = \sum_{j=1}^{\infty} d_{1j}L^j$, $d_2(L) = \sum_{j=0}^{\infty} d_{2j}L^j$, and $d_3(L^{-1}) = \sum_{k=1}^{\infty} d_{3k}L^{-k}$

	Australia	Canada	Denmark	Finland	France
α	0.169 (0.039)	0.035 (0.041)	0.070 (0.007)	0.042 (0.060)	0.010 (0.007)
β	0.386 (0.169)	0.873 (0.188)	0.789 (0.038)	0.894 (0.237)	0.942 (0.029)
d_{11}	0.214 (0.210)	0.642 (0.220)	0.147 (0.234)	0.399 (0.188)	-0.552 (0.276)
d_{12}	0.198 (0.219)	-0.342 (0.169)	-0.192 (0.222)	-0.181 (0.191)	-0.362 (0.219)
d_{13}			-0.016 (0.241)		
d_{14}			-0.633 (0.253)		
d_{21}	-0.010 (0.025)	-0.507 (0.162)	0.053 (0.197)		-0.379 (0.184)
d_{22}		0.218 (0.151)			-0.535 (0.163)
d_{23}					-0.499 (0.217)
d_{24}					-0.183 (0.194)
d_{31}	-0.274 (0.198)	0.055 (0.102)	-0.364 (0.219)	-0.718 (0.260)	-0.141 (0.153)
d_{32}	0.246 (0.200)	0.020 (0.103)	0.164 (0.222)	-0.125 (0.276)	
d_{33}					
d_{34}					
SEE	0.0131	0.0065	0.0102	0.0159	0.0061
Q(6)	11.799 (0.462)	16.129 (0.185)	11.417 (0.409)	12.048 (0.442)	8.975 (0.705)
DW	1.833	2.195	2.186	2.258	1.818
χ^2-stat for β=1	13.201 (0.001)	0.455 (0.509)	31.251 (0.000)	0.199 (0.661)	3.853 (0.068)

Table 3 -Continued:

	Greece	Iceland	Luxembourg	Sweden	U.S.
α	0.0.38 (0.011)	0.020 (0.097)	0.347 (0.034)	0.059 (0.023)	0.133 (0.026)
β	0.953 (0.048)	1.040 (0.412)	-0.254 (0.090)	0.741 (0.107)	0.304 (0.131)
d_{11}	-0.285 (0.314)	0.488 (0.193)	0.534 (0.184)	0.504 (0.228)	0.602 (0.241)
d_{12}	-0.637 (0.264)		0.235 (0.225)		-0.182 (0.287)
d_{13}	-0.554 (0.289)		-0.615 (0.183)		-0.146 (0.214)
d_{14}	-0.261 (0.326)				-0.234 (0.176)
d_{21}	0.220 (0.156)	-1.028 (0.483)	0.252 (0.170)	-0.515 (0.173)	0.447 (0.190)
d_{22}			0.094 (0.134)	0.416 (0.208)	-0.160 (0.197)
d_{23}			0.253 (0.140)		-0.199 (0.191)
d_{24}					
d_{31}	0.162 (0.134)	0.178 (0.308)	0.056 (0.128)	0.068 (0.169)	-0.107 (0.094)
d_{32}	0.321 (0.156)	0.611 (0.289)	-0.154 (0.124)	-0.419 (0.169)	
d_{33}	0.089 (0.115)		0.032 (0.134)		
d_{34}	0.278 (0.136)				
SEE	0.0119	0.0290	0.0233	0.0950	0.0047
Q(6)	7.714 (0.657)	11.020 (0.609)	15.911 (0.144)	12.394 (0.415)	6.996 (0.858)
DW	2.125	2.207	1.946	1.740	1.959
χ^2-stat for β=1	0.945 (0.354)	0.009 (0.924)	193.368 (0.000)	5.800 (0.027)	28.151 (0.000)

1. Standard errors for the estimated coefficients are given in parentheses.

2. SEE is the standard error of estimate. Q(6) is the Box-Pierce Q-statistic for autocorrelation of order 6. DW is the Durbin-Watson statistic. χ^2 is the chi-squared test statistic. The values in parentheses for the Q-statistic and the χ^2-statistic are marginal significance levels.

Essay 4:

Long-run Saving-Investment Correlations: A Revisitation With New Results

Abstract

In this paper we reexamine the long-run saving-investment relationship for six OECD countries during the fixed and flexible exchange-rate periods. In contrast to the cross-country regression approach employed by Feldstein and Horioka (1980) and others, we employ cointegration analysis to investigate the saving-investment link. This approach accounts for the non-stationarity of the underlying time series and enables us to provide evidence regarding real capital mobility at a disaggregated level, that is, for each country separately. In particular, the Johansen cointegration procedure is employed. Contrary to the conclusions of previous studies, our results indicate that there is substantial evidence of internationally mobile capital, especially during the flexible exchange-rate period.

I. Introduction

In a world of perfect capital mobility, capital flows among countries equalize the yield to investors. If such arbitrage exists, domestic saving and domestic investment in each country need not be related to each other. The implication of perfect capital mobility is a saving-investment correlation in each country which is statistically insignificant from zero. However, empirical findings indicate that domestic saving and domestic investment are highly correlated across countries and over time, thus overwhelmingly rejecting the hypothesis of perfect capital mobility.

The positive correlation between saving and investment rates was first documented by Feldstein and Horioka (1980), FH hereafter. Using data for sixteen industrial countries that are members of the Organization for Economic Cooperation and Development (OECD), FH found that a sustained increase in domestic saving has a roughly proportional long-term effect on domestic investment. They concluded that the high saving-investment correlation across these countries is inconsistent with the hypothesis of world capital market integration.[1]

The FH finding was confirmed by Feldstein (1983) for a longer time period. Subsequent research by Penati and Dooley (1984), Vos (1988), Dooley, Frankel, and Mathieson (1987), Feldstein and Bacchetta (1989), and Tesar (1991) verified the close association between domestic saving and investment rates both for industrial and

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[1] It must be noted that at least three alternative definitions of international capital mobility have been suggested in the literature besides the condition of a zero saving-investment correlation. These are covered interest rate parity, uncovered interest rate parity, and real interest rate parity. The FH condition requires real interest rate parity and that the determinants of a country's investment rate other than its real interest rate be uncorrelated with its domestic saving rate.

developing countries.[2] As a result, considerable doubt has been cast on the view that national markets for physical capital are highly integrated.[3]

Both FH and subsequent studies suffer from a number of shortcomings. First, they estimated the saving-investment relationship from a cross-country regression equation, thus ignoring the time series properties of investment and saving in each country.[4] Second, they failed to account for the non-stationarity of the underlying time series. Both saving and investment rates in each country are integrated processes of order one. Therefore, statistical estimation and inference in such a model requires a methodology which accounts for the non-stationarity of saving and investment rates. Finally, previous studies did not provide evidence for real-capital mobility at a disaggregated level, that is, for each national capital market separately. Casual empiricism suggests that real capital is more internationally mobile in some countries than in others. It is therefore of great interest to test the hypothesis of perfect capital mobility for each country separately, and if rejected, to determine the extent of capital immobility. The econometric methodology employed by FH and the others cannot address these questions.

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2 However, Murphy (1984) questioned the robustness and generality of the FH conclusion. He found weak evidence that there is some distinction between groups of large and small countries. In addition, he found that inclusion of three industrialized countries (Japan, U.K., and U.S.) in the sample biases the results against the perfect capital mobility hypothesis.

3 The interpretation of the FH finding as an indication of real capital immobility has evoked different responses. In particular, the high saving-investment correlation may be a natural response to the same exogenous forces (like population growth, productivity growth, business cycles, government policies, or barriers to commodity trade) and has therefore no bearing on the degree of capital mobility (Obstfeld (1986), Summers (1988), Murphy (1986), Finn (1990), Stockman and Tesar (1991), Baxter and Crucini (1993)). Also, Niehans (1992) provided an explanation to the high across-country correlation between saving and investment based on quadratic transaction (or risk) costs between internal and external investments.

4 Obstfeld (1986) calculated short-run time series correlations between changes in saving and investment ratios for nine OECD countries and concluded that the cross-section regression framework is inappropriate.

This paper reexamines the empirical validity of the perfect capital mobility hypothesis for six OECD countries using the FH framework.[5] In contrast to previous studies, we employ cointegration analysis to test for the existence of a long-run saving-investment relationship.[6] This technique utilizes all the information present in the time series of saving and investment in each country and accounts for their non-stationarity. By focusing on the low-frequency properties of the data, this approach eliminates the effect of cyclical variations and random shocks inherent in time series models. The presence or absence of cointegration between saving and investment rates is used as a test of the hypothesis of perfect international capital mobility for each individual economy. If the correlation between domestic saving and investment rates is indeed a long-run phenomenon, the ratios must be cointegrated. This would indicate absence of perfect international capital mobility for that country. On the other hand, absence of cointegration would imply perfect international capital mobility for the country in question. Therefore, cointegration analysis can provide evidence regarding international capital mobility for each country individually and, consequently, incorrect generalizations of results obtained from cross-section regressions can be avoided. The cointegration technique employed here is the Johansen procedure (Johansen (1988) and Johansen and Juselius (1990)). We examine the saving-investment relationship over both the fixed and flexible exchange-rate periods. For the whole sample, the cointegration results support the hypothesis of perfect capital mobility for any country in our sample except Canada, France, and Japan. The hypothesis of perfectly mobile capital cannot, however, be rejected for any country in our sample over the flexible exchange-rate period. Accordingly, our findings raise serious doubts about the

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5 The six countries chosen, Canada, France, Germany, Japan, the U.K., and the U.S., were the only ones for which sufficient quarterly time series on saving and investment were available.

6 Levy (1990) also made use of cointegration analysis to investigate the long-run relationship between a number of variables including saving and investment rates. His analysis was, however, confined to the U.S. and made use of a different data set and time period.

robustness of results from previous studies concerning the long-run relationship between saving and investment rates.

The plan of the paper is as follows. The next section describes the Johansen procedure. In section III, the data are explained and the unit root tests are presented. The Johansen cointegration results are reported in section IV. The paper concludes in section V with a summary and suggestions for further work.

II. Econometric Methodology

The Johansen procedure (Johansen (1988) and Johansen and Juselius (1990)) is employed here to examine the existence of long-term trends between saving and investment rates in six OECD countries. This cointegration technique is a full-information maximum likelihood estimation process with three major advantages over single-equation procedures. First, it examines the question of cointegration in a simultaneous-equation setting by treating all relevant variables in the system as endogenous. Accounting for the endogeneity of the time-series variables avoids the arbitrary normalization of the cointegrating vector on one of the variables imposed in the single-equation cointegrating regression. Such a normalization makes the assumption that the corresponding element in the cointegrating vector is non-zero. Second, the Johansen procedure allows one to determine the number of cointegrating relationships among the variables of interest in the system. This is contrary to the single-equation estimation procedures which cannot distinguish the existence of one or more common stationary components among the system variables.[7] Finally, the Johansen

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[7] This feature of the Johansen procedure is not particularly useful in our case since there are only two variables in the system, the domestic saving and investment rates for each country, and therefore the number of cointegrating relationships can be at most one.

procedure allows for direct testing of restrictions on the cointegrating vectors and the speed-of-adjustment coefficients.

Consider the p-dimensional vector autoregressive (VAR) process:

$$X_t = \Pi_1 X_{t-1} + \ldots + \Pi_k X_{t-k} + \varepsilon_t, \qquad t=1,2,\ldots T \tag{1}$$

where X_t is a $(px1)$ random vector of time-series variables with order of integration of at most one, ε_t is a sequence of zero-mean p-dimensional Gaussian random vectors with covariance matrix Λ, Π_i are (pxp) matrices of parameters, and $X_{-k+1}, \ldots, X_0$ are fixed. Model (1) can be expressed in first-order differences and lagged levels as follows:

$$\Delta X_t = \Theta_1 \Delta X_{t-1} + \ldots + \Theta_k \Delta X_{t-k+1} + \Pi X_{t-1} + \varepsilon_t \tag{2}$$

where $\Theta_i = -I + \Pi_1 + \ldots + \Pi_i, \qquad (i = 1, \ldots, k\text{-}1)$

$-\Pi = I - \Pi_1 + \ldots + \Pi_k$

Expression (2) will be referred to as the Vector Error Correction Model (VECM). Several specifications of the VECM are possible depending upon the deterministic components included. These specifications are:

1. $\Delta X_t = \Theta_1 \Delta X_{t-1} + \ldots + \Theta_k \Delta X_{t-k+1} + \alpha\beta' X_{t-1} + \varepsilon_t$ (no deterministic components)

2. $\Delta X_t = \Theta_1 \Delta X_{t-1} + \ldots + \Theta_k \Delta X_{t-k+1} + \alpha(\beta', \beta_0)(X_{t-1}', 1)' + \varepsilon_t$ (presence of an intercept term in levels).

3. $\Delta X_t = \Theta_1 \Delta X_{t-1} + \ldots + \Theta_k \Delta X_{t-k+1} + \alpha\beta' X_{t-1} + \mu_0 + \varepsilon_t$ (presence of an intercept term and a restricted linear trend in levels and a drift term in differences).

4. $\Delta X_t = \Theta_1 \Delta X_{t-1} + \ldots + \Theta_k \Delta X_{t-k+1} + \alpha(\beta', \beta_1)(X_{t-1}', t)' + \mu_0 + \varepsilon_t$ (presence of an intercept term and a linear trend in levels and a drift term in differences).

5. $\Delta X_t = \Theta_1 \Delta X_{t-1} + \ldots + \Theta_k \Delta X_{t-k+1} + \alpha\beta' X_{t-1} + \mu_0 + \mu_1 t + \varepsilon_t$ (presence of an intercept term, a linear trend, and a restricted quadratic trend in levels and a drift term and a linear trend in differences).

A more detailed description of the above specifications can be found in Osterwald-Lenum (1992). The different VECM specifications can be tested against each other by means of likelihood ratio (LR) tests. The distinction among the different specifications is important since the critical values when testing for the number of cointegrating relationships are different in each case.

The rank of the coefficient matrix Π on the lagged levels in (2), denoted by r, contains information about the long-run relationships among the variables in the system. If Π is a non-singular matrix, i.e., has full rank p, all elements in X_t are stationary and a VAR in levels is recommended. If the rank of Π is nullity, then all elements in X_t are first-order integrated processes and correspond to a VAR in first-differences. The interesting case occurs when $0<r<p$ which suggests the existence of r cointegrating relationships. In this case there exist (pxr) matrices α and β such that $\Pi = \alpha\beta'$. β is the matrix of cointegrating vectors and has the property that $\beta' X_t$ is stationary even though the X_t may be individually $I(1)$ processes. α is a matrix of error correction parameters and is interpreted as the speed-of-adjustment matrix toward the estimated equilibrium state.

Johansen (1988) and Johansen and Juselius (1990) have demonstrated that the maximum likelihood estimator of the cointegrating vector β is given by the eigenvector associated with the r largest, statistically significant eigenvalues of the following generalized eigenvalue problem

$$\left| \lambda S_{kk} - S_{k0} S_{00}^{-1} S_{0k} \right| = 0 \tag{3}$$

where S_{00} = the residual moment matrix from the least squares regression of ΔX_t on $\Delta X_{t-1}, \ldots, \Delta X_{t-k+1}$,

S_{kk} = the residual moment matrix from a least-squares regression of X_{t-1} on ΔX_{t-1}, ..., ΔX_{t-k+1}, and

S_{0k} = the cross-product residual moment matrix[8].

To test the hypothesis that the number of cointegrating vectors is no greater than *r*, the trace test has been proposed. More specifically, the trace test formulates the null and alternative hypotheses as

H_0: $rank(\Pi) \leq r$

H_a: $rank(\Pi) = p$,

respectively. The trace statistic is given by

$$-\ln(Q) = -T \sum_{i=r+1}^{p} \ln(1 - \hat{\lambda}_i)) \tag{4}$$

where $\hat{\lambda}_{r+1}, \ldots, \hat{\lambda}_p$ are the *(p-r)* smallest eigenvalues to the problem in (3).

The asymptotic distribution for the trace test statistic is non-standard, as it is a multivariate version of the Dickey-Fuller distribution. Critical values obtained from Monte Carlo simulations of the limiting distribution are given in Johansen and Juselius (1990) and Osterwald-Lenum (1992).

The critical assumption in the Johansen procedure is serial independence in the residual vectors of the unrestricted VECM in (2). The normality assumption is not crucial,

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8 See Johansen and Juselius (1990) and Osterwald-Lenum (1992) on how S_{00}, S_{kk}, and S_{k0} are estimated for the different specifications of the VECM in (2).

since Monte Carlo studies have demonstrated the robustness of the Johansen estimation method to deviations from normality (Gonzalo (1989)).

In addition, hypothesis testing with respect to restrictions on the cointegrating vectors can be performed. The hypotheses tested concern whether the space spanned by the estimated cointegrated vectors corresponds to the space spanned by vectors emanating from economic theory. In order to draw economically meaningful conclusions the restrictions must be imposed on all cointegrating vectors. The tests are formulated as

$$\mathrm{H}_0\colon \beta = H\phi \tag{5}$$

where H is a (pxs) matrix of constants of full rank s and ϕ is an (sxr) matrix of unknown parameters $(r \leq s \leq p)$. If $s=p$ no linear restrictions are placed upon the choice of cointegrating vectors, and if $s=r$ the cointegration space is fully specified. The likelihood ratio test statistic for testing (5) is

$$-2\ln(Q) = T\sum_{i=1}^{r}\ln\left(\frac{(1-\hat{\lambda}_i^*)}{(1-\hat{\lambda}_i)}\right) \tag{7}$$

where $\hat{\lambda}_i^*$ and $\hat{\lambda}_i$ are the r largest eigenvalues for the restricted and unrestricted models, respectively. The test statistic in (6) is distributed according to a χ^2 distribution with $r(p\text{-}s)$ degrees of freedom.

III. Data and Unit Root Tests

The data used are seasonally-adjusted nominal quarterly national-account data for the following six OECD countries: Canada, France, Germany, Japan, U.K. and U.S. The sampling period is 1960:1 to 1990:4 except for France where the sample begins from

1965:1. The source of the data is the International Monetary Fund's International Financial Statistics (IFS) data tape. Saving and investment rates are defined as ratios of gross domestic saving (S) and gross domestic investment (I) to gross domestic product (GDP), respectively. In addition to the whole sample period, we also consider the two subperiods of roughly fixed (until 1971:2) and flexible (1971:3-1990:4) exchange-rate regimes.[9] Table 1 reports the sample means of saving and investment rates over the entire period as well as the two subperiods.

Cointegration requires that both I/GDP and S/GDP be $I(1)$ for each country in our sample. Table 2 reports the results of the Augmented Dickey-Fuller (ADF) (Dickey and Fuller (1979, 1981) and Fuller (1976)) tests for the stationarity of domestic saving and investment rates for each country over the entire period and subperiods. The lag order in the ADF regression was chosen according to the Schwartz Information Criterion (SIC). The null hypothesis of a unit root cannot be rejected at the five percent level for any series except the saving rate for Canada over the entire period and the investment rate for Canada and the U.S. over the first subperiod. However, in all three cases the rejection of the unit-root null hypothesis is not robust to the choice of the lag order in the ADF regression, that is, for other lag lengths we fail to reject the unit-root null hypothesis. Consequently, the evidence suggests that each series is characterized as integrated of order one and we can, therefore, proceed to cointegration tests.

IV. Cointegration Test Results

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9 Our subsequent results are robust to the choice of the date of break.

The Johansen procedure is used in this section to investigate the existence of a long-run equilibrium relationship between domestic saving and investment rates in each of the six countries in our sample. In the present case, either investment and saving rates are cointegrated, implying the existence of international capital immobility, or they are not cointegrated indicating perfect international capital mobility. Therefore, the identifying restriction for the existence of perfect capital mobility for a country is that its saving and investment rates are not cointegrated.[10] We first present the cointegration results for the entire period and then for the subperiods of fixed and flexible exchange rates.

A. Full sample (1960:1-1990:4)

In our case, the p-dimensional vector of random variables in equation (2) is $\Delta X_t = \left(\Delta(I/GDP)_t, \Delta(S/GDP)_t\right)'$. The VECM specification we adopted allows for only an intercept term in the levels of the series (specification (2) on page 6). This specification was chosen on the basis of LR tests among the alternative specifications and appears to capture the time series properties of the data adequately (for details on the LR tests performed, see Johansen and Juselius (1990)). In order to determine the order of the VECM, we initially adopt a lag length based on the SIC criterion applied to the chosen specification. To ensure serial uncorrelatedness in the residual vectors, we perform the Box-Pierce serial correlation test on the residual series obtained from the estimation of the unrestricted VECM. If the serial independence assumption is rejected, then an additional lag is included in the VECM and the newly estimated residuals are subjected to the Box-Pierce test. This process continues until serially independent residual series are obtained. Table 3 reports the order of the VECM chosen and the corresponding Box-Pierce test

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10 It must be kept in mind that non-cointegration between saving and investment rates is a necessary but not a sufficient condition for perfect capital mobility. Saving and investment rates could become cointegrated if one or more omitted variables were added to the system.

statistics for the estimated residuals over the full sample. The lag lengths in Table 3 are the ones used for subsequent estimation and hypothesis testing.

We now proceed to investigate the rank of the impact matrix Π which contains information about the long-run relationship between saving and investment rates. Table 4 reports the trace statistics for each country over the entire period. The results of the trace test indicate that the null hypothesis of at most zero cointegrating vectors cannot be rejected at the five percent level for any country except Canada, France, and Japan. Therefore, for Germany, the U.K., and the U.S. there is no evidence of a long run relationship between saving and investment rates, thus providing support for the hypothesis of highly integrated capital markets in these economies.

For Canada the inference is that the cointegrating rank is one indicating the presence of capital immobility. Detailed cointegration results for Canada are reported in Table 5. The eigenvector corresponding to the largest eigenvalue is the cointegrating vector, which when normalized with respect to investment is $\beta'=(1, -1.53)$. Therefore, the long-run saving retention coefficient is 1.53 suggesting highly immobile international capital for Canada (a one-dollar increase in domestic saving leads to an increase in domestic investment of approximately one dollar and fifty three cents). The LR test statistic in (5) for the hypothesis of perfect capital immobility, i.e., $\beta'=(1, -1)$, is 0.866 which is significant at the 35.1 percent level. Consequently, the FH finding is supported for Canada.

Estimation of the common long-memory components of the cointegrated system for Canada provides additional insights into the saving-investment link. The common factors driving the system are estimated using the technique proposed by Gonzalo and Granger (1991). Details on the estimation of common factors and hypothesis testing associated with them are presented in the Appendix. Given that the rank of cointegration is one for Canada, there is one common factor (permanent component) driving the system. The LR test statistic for the hypothesis that the common factor of the whole system is saving, i.e., $\alpha'_{\perp}=(0,\ \phi)$ is 0.955 corresponding to a marginal significance level of 32.8 percent. We therefore conclude that for Canada a shock to saving has a permanent (long-run) effect on both saving and investment, while a shock to investment alone has only a transitory effect.

A similar analysis to the one for Canada is performed for France and Japan. For both countries the trace test statistic indicates that the cointegrating rank is one. Tables 6 and 7 report detailed cointegration results for France and Japan, respectively. The saving retention coefficients are 1.34 and 1.20 for France and Japan, respectively, indicating the presence of substantial international capital immobility for these economies. The LR test statistic for the hypothesis of perfect capital immobility, i.e., $\beta'=(1, -1)$, is 5.619 (0.017) and 1.506 (0.219) for France and Japan, respectively, with marginal significance levels given in parentheses. For both economies the FH finding is confirmed. In addition, saving appears to be the driving force for the whole system for both economies as the hypothesis that saving is the sole driving force, $\alpha'_{\perp}=(0,\ \phi)$, is not rejected (the LR test statistics are 2.802 and 0.019 for France and Japan, respectively, with corresponding marginal significance levels of 0.091 and 0.889).

B. Subperiods of Fixed and Flexible Exchange Rates

Due to structural changes in world economies, the stochastic properties of the saving-investment relationship may have changed over time. There is the widespread belief that international capital mobility increased after 1971:3 when most countries gave up the fixed exchange-rate system and allowed their currencies to float more or less freely. In this subsection we investigate this possibility by analyzing the saving-investment link for the subperiods of fixed and flexible exchange rates separately.

B1. Fixed Exchange Rates (1960:1-1971:2)

Table 8 presents the serial correlation tests performed on the residual vectors obtained from estimating the VECM of the chosen order for all countries except France over the period of fixed exchange rates (1960:1-1971:2). France is excluded from the analysis due to the limited number of observations available over this subperiod (only seven and a half years of data).

The Johansen cointegration tests statistics are reported in Table 9. The trace test, conducted at the five percent level, indicates that the null hypothesis of at most zero cointegrating vectors cannot be rejected for any country except Canada. Therefore the assumption of well-integrated capital markets is supported for the rest of the countries in our sample. For Canada the inference is that the cointegrating rank is one, suggesting restricted capital mobility.

More details with respect to the behavior of the cointegrated system for Canada is presented in Tables 10. The normalized cointegrating vector is β'=(1, -1.40) strongly evidencing the existence of completely immobile capital. The null hypothesis that saving is the common factor for the whole system, $\alpha'_{\perp}$=(0, ϕ), is not rejected (the LR test statistic takes the value of 0.333 corresponding to a marginal significance level of 56.3 percent). Therefore, a shock to saving has a permanent effect on both saving and investment for Canada.

B2. Flexible Exchange Rates (1971:3-1990:4)

We now examine the degree of integration in national capital markets during the period of flexible exchange rates (1971:3-1990:4). Table 11 presents the serial correlation tests applied to the residual vectors obtained from estimating the VECM for the chosen order for all countries in our sample.

Table 12 reports the Johansen cointegration test results for the flexible exchange-rate period. According to the trace test statistic, we fail to reject the null hypothesis of at most zero cointegrating vectors at the five percent level for all six countries in our sample. This evidence strongly supports the hypothesis of a well-integrated global capital market in the period of freely-floating exchange rates.

A comparison of the cointegration test results over the whole period and subperiods reveals some interesting insights. First, the long-run comovement between saving and investment rates for Canada observed in the fixed exchange rate period vanishes in the flexible exchange rate period. This is consistent with the popular belief that the switch of the exchange rate system from fixed to freely floating has led to an increase in the international movement of capital across national boundaries. Second, even though France is characterized by completely immobile capital over the whole period, it is not so over the flexible exchange-rate period. It appears that there was a strong saving-investment comovement for France in the pre-1971:2 period which influenced the value of the estimated saving retention coefficient over the full sample. Third, for Japan there is evidence of completely immobile capital over the whole period but not over the subperiods of fixed and flexible exchange rates. This apparent inconsistency could be attributed to lack of power of the Johansen cointegration method in small samples and therefore the results for Japan should be interpreted with caution. We consider the overall evidence for Japan as supportive of restricted capital immobility. It must be borne in mind that capital controls were in existence in Japan until 1979. Fourth, in all cases where there was a saving-investment link saving appears to be the major driving force. Finally, there is no evidence of a saving-investment relationship during the flexible exchange-rate period in any of the countries in our sample, which suggests that unrestricted capital mobility was a common feature of these economies in that period. In sum, the cointegration results indicate that the degree of capital mobility varies across countries and over time. Therefore, the evidence obtained from the FH's cross-country regression framework, which uses averages of the time-series observations over time in order to approximate the long-run or steady-state relationship between saving and investment, is not robust to more sophisticated time series methods which are better able to assess long-run correlation among economic variables.

V. Conclusions

Cointegration analysis, which analyzes the low-frequency properties of the data, enabled us to provide evidence regarding international capital mobility at a disaggregated level, that is, for each of six OECD countries separately. Our results show that with the exception of Canada, France, and Japan there is substantial evidence to support the hypothesis of perfect capital mobility. An analysis of the long-run saving-investment relationship in the subperiods of fixed and flexible exchange rates reveals that there was an increase in the degree of capital mobility in the flexible exchange-rate period. In particular, there is strong evidence in support of the perfect capital mobility hypothesis in all countries in our sample during the flexible exchange-rate period. Therefore the high saving-investment correlation found in empirical studies by FH and others is not robust to the time series methodology employed here and the cross-section regression framework is inappropriate.

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Appendix

If a system of $I(1)$ series is cointegrated with cointegrating rank r, then there are $m=(p-r)$ $I(1)$ common factors which are the driving forces of the cointegrated system. In other words, the cointegrated system has the following common factor representation:

$$X_t = A_1 f_t + A_2 z_t \tag{Ap.1}$$

where f_t is a $(mx1)$ common factor matrix, $z_t = \beta' X_t$ with β being the cointegration matrix, and A_1 and A_2 are loading matrices. Once the rank of the cointegration matrix is estimated, the only unknown in equation (Ap.1) is f_t, since A_1 will be any basis of the left null space of β'. Gonzalo and Granger (1991) suggest the following two conditions to identify the common factor matrix f_t. The first condition restricts the elements of f_t to be linear combinations of the variables in the system, that is, $f_t = B X_t$. The second condition requires that $A_1 f_t$ and $A_2 z_t$ form permanent and transitory components of X_t, respectively, according to the following definition:

Definition: Let X_t be a difference stationary process. A permanent-transitory decomposition for X_t is a pair of stochahstic processes P_t and T_t, such that

(i) P_t is difference stationary and T_t is covariance stationary

(ii) $Var(\Delta X_t) > 0$ and $\mathrm{var}(T_t) > 0$

(iii) $X_t = P_t + T_t$

(iv) $\lim_{h\to\infty} \dfrac{\partial E_t(X_{t+h})}{\partial \varepsilon_{P_t}} \neq 0$ and

$$\lim_{h\to\infty} \frac{\partial E_t(X_{t+h})}{\partial \varepsilon_{T_t}} = 0$$

where E_t is the conditional expectation with respect to the past history, and ε_{P_t} (ε_{T_t}) is the part of innovations in P_t (T_t) that is orthogonal to the innovations in T_t (P_t).

By imposing the identifiying conditions the common factors can be easily estimated from the VECM in (2) as

$$f_t = \alpha_\perp{}' X_t$$

where $\alpha_\perp$ is (mxp) and $\alpha_\perp{}' \alpha = 0$.

Given that the cointegrating rank is r, the maximum likelihood estimator of $\alpha_\perp$ can be found by solving the following generalized eigenvalue problem:

$$|\theta S_{oo} - S_{ok} S_{kk}^{-1} S_{ko}| = 0 \qquad \text{(Ap.2)}$$

where Π in equation (2) has been preplaced with $\Pi = \alpha\beta'$. The choice of $\hat{\alpha}_\perp$ is the eigenvector associated with the m smallest eigenvalues of the problem in (Ap.2).

Restrictions on the common factors can also be formed and tested. Let G be a $(p \times n)$ restriction matrix and ϕ be an $(n \times m)$ matrix of unknown parameters. Then the hypotheses on $\alpha_\perp$ can be formed as:

$$\alpha_\perp = G\phi \qquad \text{(Ap.3)}$$

The estimate of ϕ is the eigenvectors associated to the n smallest eigenvalues of the problem:

$$|\theta G' S_{oo} G - G' S_{ok} S_{kk}^{-1} S_{ko} G| = 0 \qquad \text{(Ap.4)}$$

Given that the cointegration rank is r, the likelihood ratio statistic of the hypothesis in (Ap.3) is given by:

$$T\sum_{i=r+1}^{p} \ln \frac{(1-\tilde{\theta}_{i+n-p})}{(1-\hat{\theta}_i)} \qquad \text{(Ap.5)}$$

and distributed as standard χ^2 with $(p\text{-}r)\times(p\text{-}n)$ degrees of freedom.

Table 1: Mean Values of Saving and Investment Ratios

Country	1960:1-1990:4		1960:1-1971:2		1971:3-1990:4	
	S/GDP	I/GDP	S/GDP	I/GDP	S/GDP	I/GDP
Canada	0.235	0.210	0.234	0.183	0.235	0.227
France[a]	0.234	0.222	0.259	0.212	0.226	0.226
Germany	0.261	0.224	0.286	0.235	0.247	0.217
Japan	0.339	0.322	0.356	0.332	0.329	0.316
U.K.	0.179	0.170	0.185	0.141	0.176	0.187
U.S.	0.185	0.186	0.189	0.168	0.183	0.196

[a] The whole period for France is from 1965:1 to 1990:4.
The first subperiod is therefore from 1965:1 to 1971:2.

Table 2: Augmented Dickey-Fuller Unit Root Test Results [a]

Country	ADF Test Statistic [b,c] 1960:1-1990:4 (T=124) S/GDP	I/GDP	1960:1-1971:2 (T=46) S/GDP	I/GDP	1971:3-1990:4 (T=78) S/GDP	I/GDP
Canada	[0] -1.915	[8] -3.721**	[1] -1.058	[0] -6.972***	[1] -3.045	[0] -0.963
France	[1] -1.483	[5] -1.844	–	–	[1] -0.665	[0] -0.043
Germany	[3] -1.039	[3] -2.414	[4] -3.448*	[5] -2.132	[0] -1.446	[0] -1.684
Japan	[0] -1.788	[1] -2.624	[0] -1.936	[0] -2.507	[0] -1.239	[1] -0.525
U.K.	[0] -3.322*	[8] -2.955	[0] -3.916*	[1] -3.336*	[0] -2.951	[0] 0.117
U.S.	[1] -2.451	[5] -2.506	[0] -2.244	[0] -4.802***	[0] -2.407	[2] -2.205

[a] The sample period for France is from 1965:1 to 1990:4 (T=104). The ADF test was not performed for France for the first subperiod (1965:1-1971:2) due to the limited number of observations available. The number in brackets is the lag order in the ADF regression chosen according to the Shwartz Information Criterion (SIC).

[b] For each of the series, y_t, the following ADF regression is run:

$$\Delta y_t = \gamma + \delta t + \varphi y_{t-1} + \sum_{i=1}^{j} \psi_i \Delta y_{t-i} + \varepsilon_t$$

where Δ is the first-difference operator, t is a time trend, j is the lag order chosen according to the SIC criterion, and ε_t is a stationary random error. The SIC value is given by the formula $\log|\hat{\Sigma}| + \left(\frac{\log T}{T}\right)d$ where $\hat{\Sigma}$ is the estimated innovation matrix, T is the sample size, and d is the number of parameters estimated in the ADF regression. The null hypothesis of non-stationarity is rejected when φ is significantly negative.

[c] The ADF critical values, provided below, are derived from MacKinnon's (1991) response surface estimates of critical values as applied to various sample sizes.

Level	T=124	T=104	T=46	T=78
1%	-4.034	-4.049	-4.168	-4.079
5%	-3.446	-3.453	-3.509	-3.467
10%	-3.148	-3.152	-3.184	-3.160

Significance Levels: * = 10 per cent, ** = 5 per cent, *** = 1 per cent.

Table 3: Serial Correlation Tests for the Vector Error Correction Model (VECM) Residuals (1960:1-1990:4) [a]

		BP(10) [b]	
Country	Order of VECM	Investment Equation	Saving Equation
Canada	[3]	5.383 (0.864)	7.071 (0.719)
Canada	[2]	3.492 (0.967)	11.193 (0.343)
France	[3]	10.583 (0.391)	9.919 (0.448)
Germany	[1]	11.241 (0.339)	5.034 (0.889)
Japan	[2]	3.871 (0.953)	17.656 (0.061)
U.K.	[5]	5.544 (0.852)	5.806 (0.831)
U.S.	[4]	5.467 (0.857)	4.288 (0.933)

[a] The sample period for France is from 1965:1 to 1990:4.

[b] BP(10) is the Box-Pierce test statistic for autocorrelation of order 10 in the VECM residuals. The marginal significance level is given in parentheses.

Table 4: Johansen Cointegration Test (1960:1-1990:4) [a]

		Trace Test Statistic[b]	
Country	Order of VECM	H_0: r=0	H_0: r≤1
Canada	[3]	31.209***	8.283
France	[2]	51.812***	2.383
Germany	[3]	14.231	2.131
Japan	[1]	19.999**	3.332
U.K.	[2]	15.926	3.257
U.S.	[5]	15.912	4.775

[a] The sample period for France is from 1965:1 to 1990:4.

[b] The alternative hypothesis is that the impact matrix P is full rank, that is, r=2.
The critical values are as follows (Osterwald-Lenum (1992)):

Level	r=0	r≤1
1%	24.60	12.97
5%	19.96	9.24
10%	17.85	7.52

Significance Levels: * = 10 per cent, ** = 5 per cent, *** = 1 per cent.

Table 5: Detailed Cointegration Results for Canada over the Full Period (1960:1-1990:4)

Eigenvalues

0.173	0.066	0.000

Eigenvectors

1.000	1.000	1.000
-1.529	-0.177	-0.908
0.115	-0.196	-0.096

Common Factor Matrix

185.711	50.561
-25.888	141.313

Table 6: Detailed Cointegration Results for France over the Full Period (1965:1-1990:4)

Eigenvalues

0.386	0.023	0.000

Eigenvectors

1.000	1.000	1.000
-1.340	1.134	0.044
0.074	-0.464	-0.281

Common Factor Matrix

246.422	69.401
-36.811	163.775

Table 7: Detailed Cointegration Results for Japan over the Full Period (1960:1-1990:4)

Eigenvalues

0.127	0.026	-0.000

Eigenvectors

1.000	1.000	1.000
-1.202	0.255	-1.053
0.051	-0.420	-0.076

Common Factor Matrix

186.873	7.302
-27.537	144.026

Table 8: Serial Correlation Tests for the Vector Error Correction Model (VECM) Residuals over the Fixed Exchange Rate Period (1960:1-1971:2)

		BP(10)[a]	
Country	Order of VECM	Investment Equation	Saving Equation
Canada	[4]	2.313 (0.993)	6.017 (0.814)
Germany	[2]	13.824 (0.181)	8.194 (0.610)
Japan	[1]	8.650 (0.566)	2.190 (0.995)
U.K.	[2]	5.987 (0.816)	8.963 (0.536)
U.S.	[5]	5.816 (0.830)	9.867 (0.452)

a BP(10) is the Box-Pierce test statistic for autocorrelation of order 10 for the VECM residuals. The marginal significance level is given in parentheses.

Table 9: Johansen Cointegration Test over the Fixed Exchange Rate Period (1960:1-1971:2)

		Trace Test Statistic[b]	
Country	Order of VECM	H_0: r=0	H_0: r≤1
Canada	[4]	20.360**	4.750
Germany	[2]	15.343	2.266
Japan	[1]	19.046*	1.751
U.K.	[2]	18.976	6.412
U.S.	[5]	19.652	4.104

a The alternative hypothesis is that the impact matrix Π is full rank, that is, r=2.
See Table 4 for critical values.

Significance Levels: * = 10 per cent, ** = 5 per cent, *** = 1 per cent.

Table 10: Detailed Cointegration Results for Canada over the Fixed Exchange Rate Period (1960:1-1971:2)

Eigenvalues

0.316	0.109	0.000

Eigenvectors

1.000	1.000	1.000
-1.401	-0.280	-0.480
0.085	-0.177	-0.157

Common Factor Matrix

153.320	29.107
-43.057	196.300

Table 11: Serial Correlation Tests for the Vector Error Correction Model (VECM) Residuals over the Flexible Exchange Rate Period (1971:3-1990:4)

		BP(10)[a]	
Country	Order of VECM	Investment Equation	Saving Equation
Canada	[1]	8.984 (0.534)	6.752 (0.749)
Canada	[3]	6.571 (0.765)	5.265 (0.873)
France	[3]	14.299 (0.160)	9.485 (0.487)
Germany	[1]	8.712 (0.560)	5.039 (0.888)
Japan	[2]	5.541 (0.852)	7.746 (0.654)
U.K.	[1]	3.053 (0.980)	6.043 (0.812)
U.S.	[4]	5.467 (0.857)	4.288 (0.933)

[a] BP(10) is the Box-Pierce test statistic for autocorrelation of order 10 in the VECM residuals. The marginal significance level is given in parentheses.

Table 12: Johansen Cointegration Test over the Flexible Exchange Rate Period (1971:3-1990:4)

		Trace Test Statistic[a]	
Country	Order of VECM	H_0: r=0	H_0: r≤1
Canada	[1]	22.379	4.376
France	[3]	23.115*	6.377
Germany	[3]	14.376	4.455
Japan	[1]	21.001	8.120
U.K.	[2]	11.460	3.719
U.S.	[1]	13.548	5.465

[a] The alternative hypothesis is that the impact matrix Π is full rank, that is, r=2. See Table 4 for critical values.

Significance Levels: * = 10 per cent, ** = 5 per cent, *** = 1 per cent.