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Estimating the Permanent and Transitory Components of the UK Business Cycle

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ABSTRACT

We estimate a model that incorporates two key features of business cycles, comovement among economic variables and switching between regimes of boom and slump, to quarterly UK data for the last four decades. Common permanent and transitory factors, interpreted as composite indicators of coincident variables, and estimates of turning points from one regime to the other, are extracted from the data by using the Kalman filter and maximum likelihood estimation. Both comovement and regime switching are found to be important features of the UK business cycle. The components produce sensible representations of the cycles and the estimated turning points agree fairly well with independently determined chronologies.

1. INTRODUCTION

THE TWO EMPIRICAL regularities of business cycles highlighted by Burns and Mitchell (1946) — comovement among economic variables through the cycle and asymmetry in the evolution of the cycle — have undergone a resurgence of interest in recent years, prompted by the development of new time series techniques. Two of the most influential models of the business cycle are Stock and Watson's (1989, 1991, 1993, 1999) linear common factor model and Hamilton's (1989) regime switching model. Stock and Watson develop a linear dynamic factor model where business cycles are measured by comovements in various components of economic activity. Using several macroeconomic time series, they extract a single unobserved variable and interpret it as the 'state of the economy'. They then compare this variable with the US Department of Commerce (DOC) composite index, and find that the similarity between the two is striking, especially over the business-cycle horizon. The disadvantage of their model, however, is that its linearity cannot capture business cycle asymmetry, and forces expansions and contractions to have the same amplitude and duration.

To capture such asymmetry, Hamilton (1989) develops a regime switching model in which output growth switches between two states according to a first order Markov process. Expansions can therefore be gradual and drawn out while recessions may be shorter and steeper — the 'stylised facts' of modern business cycles. Applying this model to the US, he shows that shifts between positive and negative output growth accord well with the NBER's chronology of business cycle peaks and troughs. Being based on a single time series, however, Hamilton's model cannot capture the notion of economic fluctuations corresponding to comovements of many aggregate and sectoral variables. It may well be impossible for only one coincident variable to capture all underlying business cycle information, which is the conclusion of both Filardo (1994) and Diebold and Rudebusch (1996).

Indeed, Diebold and Rudebusch provide both empirical and theoretical support for combining these two key features of the business cycle, although they do not fully estimate a model. Building on this research, however, several studies estimate these two features simultaneously within the regime switching common factor model. Examples are Chauvet (1998), Kim and Yoo (1995), and Kim and Nelson (1998), who use US data, and Mills and Wang (2002a), who use UK data. The common factor is defined to be an unobserved variable that summarises the common cyclical movements of a set of coincident macroeconomic variables, as in Stock and Watson (1991). However, this common factor is also subject to discrete shifts so that it can capture the asymmetric nature of business cycle phases, as in Hamilton (1989). Within a multivariate framework, all papers report that inferences about the state of the economy obtained from the model exhibit significantly higher correlations with the NBER reference dates than if just a single variable, such as output growth, was used.

The basic idea behind these studies is that information about business cycles can be extracted from a group of series rather than a single series, so that estimated business cycles reflect information from various economic sectors. Furthermore, the extracted factor can be compared with, for example, the DOC coincidence index, and more importantly, it can be used for real time assessment of the economy.

One problem associated with this framework is that the models cannot capture the peak-reversion feature, or 'plucking behaviour', of business cycle movements, first suggested by Milton Friedman more than 30 years ago. Friedman (1964, 1993) pointed out that the amplitude of cyclical contractions in US output tended to be strongly correlated with succeeding expansions, but that these expansions were uncorrelated with the amplitude of subsequent contractions, thus producing an asymmetry between succeeding phases of the business cycle. Friedman (1993) provides some basic statistical evidence to support the plucking model.

Kim and Nelson (1999) propose a framework that enables both asymmetry and an output ceiling to be captured within a single model containing shifts in regime. Their nonlinear model incorporates asymmetric movements of output away from trend and asymmetric persistence of shocks during recessionary and normal times. This framework is able to estimate the importance of downward shocks to both trend and cycle, and to test the plucking hypothesis against symmetric trend-plus-cycle alternatives such as Clark (1987). Kim and Nelson show that the stochastic behaviour of US output is well characterised by Friedman's plucking model, i.e., output is occasionally plucked down by recession and the cyclical or transitory component exhibits asymmetric behaviour. Mills and Wang (2002b) further extend the analysis to the G7 countries and find a variety of results.

While Kim and Nelson (1999) focus only on a single variable, that of output, in this paper we utilise the approach of Kim and Murray (2002), which allows for regime switching common permanent and transitory components within a multivariate framework. We think that this extension is important for three related reasons. First, if a set of indicators can correctly provide signals of changes in aggregate economic activity, then this would be helpful to any business or government in their decision making, since they are typically affected by economic expansions and contractions. Second, in studying aggregate fluctuations like business cycles, it is useful to be able to analyse a group of important economic time series. Individual series measure only one aspect of economic activity, so they cannot capture the idea of cyclical fluctuations corresponding to comovements of many aggregate and sectoral variables. Third, if there is a transitory component that plucks the economy down then, as suggested by Sichel (1994), there may exist a high-growth recovery phase following a recession. Knowledge of these features for the UK economy is therefore important for both policy makers and forecasters.

The rest of the paper is organised as follows. In section 2 we illustrate the multivariate dynamic factor model which incorporates independent regime switching of permanent and transitory components. The data sets used in our analysis are introduced in Section 3, where we also report the empirical results of our modelling exercises. Section 4 draws implications and concludes.

2. Model specification

Following Kim and Murray (2002), suppose that Y_{it} is (the logarithm of) a macroeconomic variable that moves contemporaneously with overall economic conditions. It can be modelled as consisting of three stochastic autoregressive processes — a single unobserved permanent component, c_t, a single unobserved transitory component, x_t, and an idiosyncratic component, z_t. Defining $\Delta y_{it} = \Delta\left(Y_{it} - \overline{Y}_i\right)$, where $\overline{Y}_i$ is the sample mean of Y_{it}, the model can be written as follows

$$\Delta y_{it} = \gamma_i \Delta c_t + \lambda_i \Delta x_t + z_{it} \qquad i = 1,....,n \tag{1}$$

Δc_t is the demeaned growth rate of the common permanent component, which is dependent on whether the economy is in expansion or recession, and it enters each of the n equations with a different weight γ_i, which measures the sensitivity of the ith variable to the common permanent component. Similarly, the factor loadings λ_i indicate the extent to which each series is affected by the common transitory component, Δx_t. The variables z_{it} are made up of the idiosyncratic permanent and transitory components.

To incorporate the asymmetry of business cycles, the common permanent component is assumed to be generated by a Markov switching process of the type proposed by Hamilton (1989), so that

$$\phi(L)\Delta c_t = \mu_{S_{1t}} + v_t \qquad v_t \sim i.i.d.\, N(0,1) \tag{2}$$

$$\mu_{S_{1t}} = \mu_0\left(1 - S_{1t}\right) + \mu_1 S_{1t}$$

where S_{1t} is an unobservable state variable that switches between state 1 (recession) and state 0 (expansion) with transition probabilities governed by the first-order Markov switching process

$$\begin{aligned} P\left[S_{1t} = 0 \middle| S_{1,t-1} = 0\right] &= p_1 \\ P\left[S_{1t} = 1 \middle| S_{1,t-1} = 1\right] &= q_1 \end{aligned} \tag{3}$$

To capture peak-reversion behaviour, the common transitory component is subject to the type of regime switching advocated by Kim and Nelson (1999):

$$\phi^*(L)x_t = \pi_{S_{2t}} + u_t \qquad\qquad u_t \sim i.i.d.\,N(0,1) \tag{4}$$

$$\pi_{S_{2t}} = \pi S_{2t}, \quad \pi \neq 0$$

Here π_{S2t} is an asymmetric discrete shock, which is dependent upon an unobserved variable, S_{2t}, an indicator variable that switches between state 1 (recession) and state 0 (expansion) and also evolves according to a first-order Markov-switching process:

$$\begin{aligned} P\left[S_{2t} = 0 \middle| S_{2,t-1} = 0\right] &= p_2 \\ P\left[S_{2t} = 1 \middle| S_{2,t-1} = 1\right] &= q_2 \end{aligned} \tag{5}$$

where S_{2t} is independent of S_{1t}. During 'normal times', $S_{2t} = 0$ and the economy is near to potential or trend output. During 'recessions', however, $S_{2t} = 1$ and the economy is hit by a transitory shock and plucked down by the size of π ($\pi < 0$). The idiosyncratic components are assumed to have autoregressive representations,

$$\psi_i(L)z_{it} = \varepsilon_{it}, \qquad\qquad \varepsilon_{it} \sim i.i.d.\,N\left(0,\sigma_i^2\right) \tag{6}$$

The innovations ε_{it} can be thought of as measurement errors, while v_t and u_t are the innovations to the common permanent and transitory components, respectively. The functions $\psi_i(L)$, $\phi(L)$ and $\phi*(L)$ are polynomials in the lag operator L, whose roots all lie outside the unit circle, and Δ=1$-L$. For the identification of the model, it is assumed that the variances of v_t and u_t are unity. The innovations v_t, u_t and ε_{it} are assumed to be independent for all t and i.

The model can be thought of as a generalised dynamic factor model, and has been estimated by Kim and Murray (2002) using US data. With appropriate restrictions, it can reproduce many of the models that have appeared in the literature. For example, if n = 1, it is a univariate model and with π = 0, we have Hamilton's (1989) model. With μ_1 = 0, we have Kim and Nelson's (1999) model. If $n > 1$, it becomes a multivariate model. In the absence of equation (4) (or equivalently with $\lambda_i = 0$ in (1)), we have the Diebold and Rudebusch (1996) model that has been estimated by Chauvet (1998), Kim and Yoo (1995), and Kim and Nelson (1998) for the US, and by Mills and Wang (2002a) for the UK On the other hand, in the absence of equations (2) and (4), we have the Stock and Watson (1989, 1991, 1993) linear dynamic factor model.

The common permanent and transitory components thus depend upon two different state variables, so that a recession can arise from either a regime switch in Δc_t or a 'pluck' in Δx_t. In addition, the timing and duration of S_{2t} and S_{1t} are allowed to vary across recessions. Note that the two common factors are not separately identified if the permanent and transitory factor loadings are equal ($\gamma_i = \lambda_i$) and if they are governed by the same state variable ($S_{2t} = S_{1t}$).

To facilitate estimation, the model can be given a state-space representation. With AR(1) processes for the common permanent and transitory components and the idiosyncratic term, and with $n = 4$ (as in the application below), the model can be expressed as the measurement and transition equations

Measurement equation

$$\begin{bmatrix} \Delta y_{1t} \\ \Delta y_{2t} \\ \Delta y_{3t} \\ \Delta y_{4t} \end{bmatrix} = \begin{bmatrix} \gamma_1 & \lambda_1 & -\lambda_1 & 1 & 0 & 0 & 0 \\ \gamma_2 & \lambda_2 & -\lambda_2 & 0 & 1 & 0 & 0 \\ \gamma_3 & \lambda_3 & -\lambda_3 & 0 & 0 & 1 & 0 \\ \gamma_4 & \lambda_4 & -\lambda_4 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta c_t \\ x_t \\ x_{t-1} \\ z_{1t} \\ z_{2t} \\ z_{3t} \\ z_{4t} \end{bmatrix} = H\xi_t \tag{7}$$

Transition equation

$$\begin{bmatrix} \Delta c_t \\ x_t \\ x_{t-1} \\ z_{1t} \\ z_{2t} \\ z_{3t} \\ z_{4t} \end{bmatrix} = \begin{bmatrix} \mu_{S_{1t}} \\ \pi_{S_{2t}} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} \phi_1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \phi_1^* & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \psi_1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \psi_2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \psi_3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \psi_4 \end{bmatrix} \xi_{t-1} + \begin{bmatrix} v_t \\ u_t \\ 0 \\ \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix} = \alpha_{S_t} + F\xi_{t-1} + V_t$$

where $\quad E(V_t V_t') = Q$

and

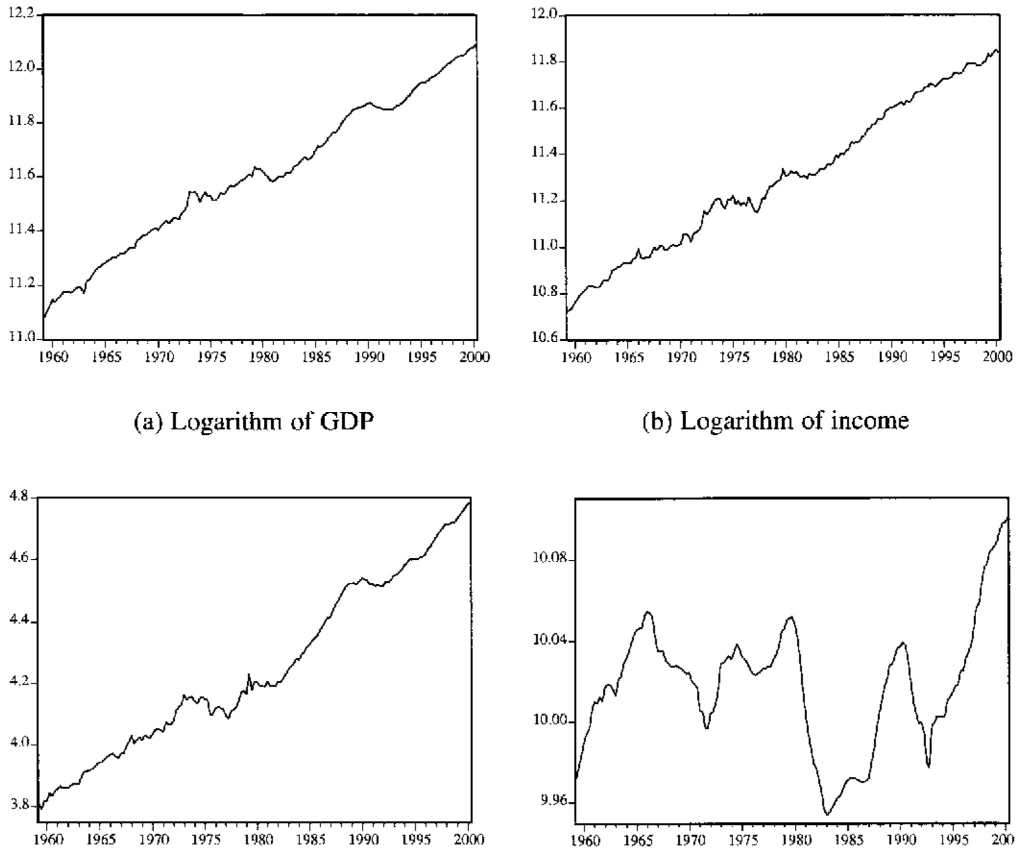
$$Q = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \sigma_4 \end{bmatrix} \tag{8}$$

With the availability of the estimation method developed by Kim (1994), the state space model can be estimated by maximising the likelihood function. Inferences about the unobserved nonlinear permanent and transitory components and the latent Markov state variables can then be obtained at the same time. The method consists of a combination of Hamilton's algorithm and the nonlinear discrete version of the Kalman filter: see Kim (1994) for technical details.[2]

3. Data and Results

We chose four time series that are representative coincident economic indicators: output, income, sales and employment. These series are GDP at factor cost, real household disposable income, retail sales, and employee jobs. All series are seasonally adjusted quarterly observations and logarithms are used.[3] The sample period is from 1959Q2 to 2000Q2. Graphs of the four series are shown in Figure 1.

Figure 1: Time series of the four coincident variables



(a) Logarithm of GDP

(b) Logarithm of income

(c) Logarithm of sales

(d) Logarithm of employee jobs

We first test whether the four series are individually integrated and, if they are, whether they are cointegrated.[4] We find that we cannot reject the hypothesis that each of the series is integrated, and neither can we reject the hypothesis of no cointegration among these variables. Therefore, we use the first differences of the variables (multiplied by one hundred) as is implied by the model set out in equations (1), (2), (4) and (6). As indicated in section 2, all series are demeaned by subtracting the sample mean from each difference.

For the model specification, we initially fitted AR(2) processes for the common permanent and transitory components and the four idiosyncratic components in equations (2), (4) and (6). In all cases, however, estimates of the second-order autoregressive coefficients were insignificant. We therefore chose a parsimonious AR(1) representation for all components, producing the estimates presented in Table 1. Before discussing our results, a further diagnostic test was carried out to assess the robustness of these estimates. We estimated the model with the restriction $S_{1t} = S_{2t}$, which assumes that both permanent and transitory components switch at the same time. Under this restriction, we obtain the estimates shown in Table 2.

Table 1: Estimates of the dynamic common permanent and transitory model with Markov switching ($S_{1t} \neq S_{2t}$)

Common permanent component

ϕ_1	μ_0	μ_1	p_1	q_1
0.4458	0.3302	-1.5636	0.9669	0.8319
(0.1254)	(0.1376)	(0.4360)	(0.0208)	(0.0871)

Common transitory component

ϕ_1^*	π	p_1	q_1
0.9477	-4.2406	0.9718	0.3845
(0.0201)	(0.8486)	(0.0144)	(0.2070)

Idiosyncratic component and factor loadings

	ψ_i	σ_i	λ_i	γ_i
Δy_{1t}	-0.0595	0.8174	0.3132	0.2460
	(0.0865)	(0.0504)	(0.0711)	(0.0554)
Δy_{2t}	-0.3441	0.8235	0.3515	0.1250
	(0.0795)	(0.0527)	(0.0613)	(0.0421)
Δy_{3t}	-0.5831	0.5307	0.5261	0.1648
	(0.0993)	(0.0789)	(0.0803)	(0.0421)
Δy_{4t}	-0.0877	0.4069	0.0523	0.5617
	(0.2458)	(0.1375)	(0.0601)	(0.1086)
Log-likelihood	-368.788			

Note: The order of the variables in y_{it} is GDP, income, sales and employment. Standard deviations are in parentheses.

Several of the parameter estimates now become insignificant and a comparison of the two models produces a likelihood ratio of 11.6. Although standard critical values are not appropriate here, the combination of such a high likelihood ratio for the imposition of one restriction, coupled with the poorer set of restricted estimates, leads us to prefer the unrestricted model, which implies that the common permanent and transitory components switch at different times. Consequently, our discussion is based on the estimates reported in Table 1.

Table 2: Estimates of the dynamic common permanent and transitory model with Markov switching (S_{1t}=S_{2t})

Common permanent component

ϕ_1	μ_0	μ_1	p_1	q_1
0.6081	0.2837	-1.2093	0.9464	0.8172
(0.1664)	(0.1523)	(0.4793)	(0.0331)	(0.1061)

Common transitory component

ϕ_1^*	π	p_2	q_2
0.9330	-1.4350	-	-
(0.0271)	(0.4034)		

Idiosyncratic component and factor loadings

	ψ_i	σ_i	λ_i	γ_i
Δy_{1t}	-0.0685	0.8094	0.4047	0.1515
	(0.0882)	(0.0508)	(0.0600)	(0.0616)
Δy_{2t}	-0.3299	0.8285	0.3992	0.0297
	(0.0797)	(0.0521)	(0.0590)	(0.0450)
Δy_{3t}	-0.5861	0.5340	0.6236	0.0278
	(0.1057)	(0.0896)	(0.0838)	(0.0562)
Δy_{4t}	-0.0605	0.4672	0.1009	0.5106
	(0.2205)	(0.1543)	(0.0778)	(0.1489)

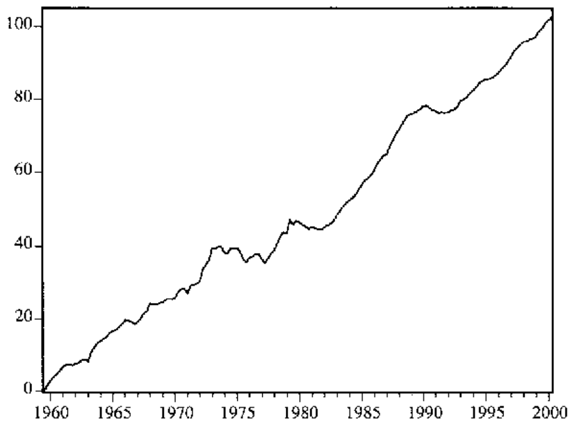
Log-likelihood -374.605

Note: The order of the variables in y_{it} is GDP, income, sales and employment. Standard deviations are in parentheses.

Note first that a comparison of the estimates of the two sets of factor loadings shows that it is highly unlikely that $\gamma_i = \lambda_i$ for all i, so that, when allied with the results of Table 2, we are confident that the model is identified. The estimated model seems successful in extracting information about fluctuations in economic activity. Both common permanent and transitory components exhibit first order autocorrelation as the estimates of ϕ_1 and ϕ_1^* are significant at the 1 per cent level. Consider first the common permanent component. The results support the presence of asymmetric business cycles that switch between two different states, with state 1 having a significantly negative mean and state 0 a significantly positive mean. The transition probabilities associated with these two regimes of recession and expansion are 0.832 and 0.967 respectively. These estimates imply that the average duration of the expansionary regime is $(1\text{-}p_1)^{-1} = 30.3$ quarters, which may be contrasted with $(1\text{-}q_1)^{-1} = 6$ quarters for the average duration of the recessionary regime.

Since the mean of Δc_t is 0.63, equivalent to a 'trend' growth of 2½ per cent per annum, the estimates of μ_0 and μ_1 imply mean growth rates of the business cycle common permanent component in the two regimes of 0.63-1.56 = -0.93 and 0.63+0.33 = 0.96, i.e., approximately ±3¾ per cent per annum. Therefore, since $q_1 < p_1$ and $|\mu_1| > |\mu_0|$, recessions on average are both steeper and shorter than expansions. Figure 2 plots the extracted Markov switching common permanent component.[5] This series accurately reproduces the stylised facts of the post-war UK growth experience, that is, the volatility of the 1970s and the relative stability of the 1990s. Regarding the factor loadings indicated by the γ_i, they are all significant, suggesting that these macroeconomic variables are explained by the common permanent component of business cycles. As each loading is positive, all variables move pro-cyclically. This is not surprising and is in agreement with conventional views of the business cycle (see, for example, Dow, 1998). Our estimates show that employment has the highest factor loading, followed by output, sales and income.

Figure 2: Extracted Markov switching common permanent component

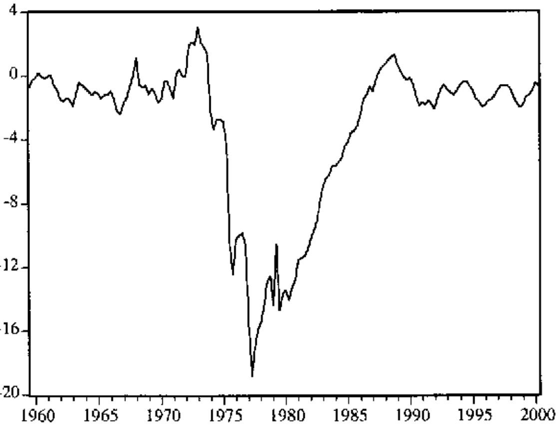


Common permanent factor, c_t

On the other hand, the estimated common transitory component is consistent with peak-reversion behaviour of the business cycle, as the plucking term, π, is significantly negative, thus supporting Friedman's hypothesis that the economy is temporarily plucked down by negative shocks. The estimated transition probabilities are 0.972 and 0.385 for expansions and recessions, respectively. Therefore, the average durations of the expansionary and recessionary regimes are 35.7 and 1.6 quarters respectively, thus producing an even sharper contrast than the transition probabilities from the common permanent component. As far as the factor loadings,

λ_i, are concerned, they are all significant except λ_4, which corresponds to employment, implying that the common transitory component also plays a significant role in explaining business cycle fluctuations. Sales have the highest factor loading, followed by income, output and employment, suggesting that declines in sales are the major factor in producing temporary negative shocks to the economy. Figure 3 plots the common transitory component. It clearly shows that a succession of transitory shocks played a major role during the recessions of the 1970s and 1980s, but that they were less of a factor in the recesssion of the early 1990s.

Figure 3. Extracted Markov switching common transitory component

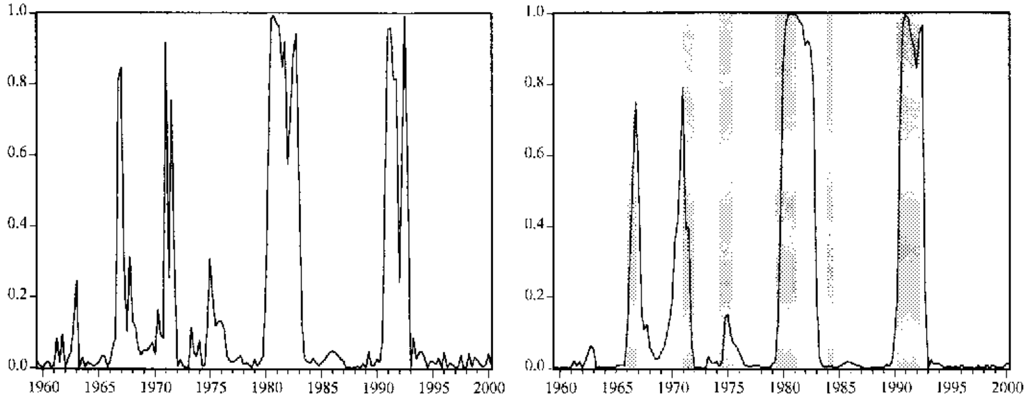


Common transitory factor, x_t

Moving to the idiosyncratic component, the negative coefficients of ψ_i indicate that the idiosyncratic components of these series exhibit negative serial correlation. While income has the highest innovation variance among the four variables, employment has the smallest.

Figures 4 and 5 plot the probabilities that the economy is in a recession: panel (a) shows the filtered probability conditional on information available through t, $\Pr\left[S_{it}=1\middle|\Psi_t\right]$, $(t=1,2,\cdots,T)$, $(i=1,2)$ while panel (b) shows the smoothed probability based on the complete set of information up to T, $\Pr\left[S_{it}=1\middle|\Psi_T\right]$, $(t=1,2,\cdots,T)$, $(i=1,2)$. While the two pairs of filtered and smoothed graphs are very similar, the timing and duration of the permanent and transitory components are different. As there is no official UK business cycle chronology that we may relate our results to, we have thus compared our inferred probabilities of recession with the chronology provided by Artis, Kontolemis and Osborn (1997).[6] Their dating is based on monthly industrial production and finishes in 1993, and so can only be used for rough comparisons. For the permanent component, we find that our recession probabilities are closely related to their dating. This component clearly picks out and dates correctly the several major recessions that the UK economy has experienced during the last four decades, which are shown as shaded areas on plot (b) of Figure 4. For the transitory component, however, the recession probabilities only pick up the recessions of the 1970s, and totally miss the recession in the early

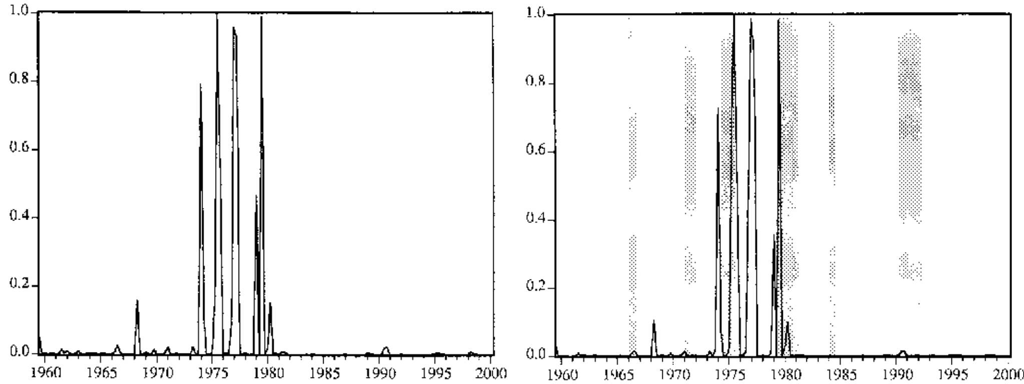
Figure 4: Filtered and smoothed recession probability of common permanent component



(a) Filtered probability (b) Smoothed probability

1990s. Interestingly, Birchenhall, Osborn and Sensier (2001), using a logistic model, have dated the major classical troughs of GDP to be 1975Q2, 1981Q1 and 1992Q2. It can be seen from Figures 4 and 5 that the first of these is identified via the transitory component, whereas the other two are picked up by the permanent component. The commonly held view is that the mid-1970s recession was a consequence of oil price shocks. These results suggest that such shocks impacted upon the transitory component of the business cycle, in contrast to the structural shocks of the early 1980 and 1990s, which impacted upon the permanent component of the cycle.

Figure 5: Filtered and smoothed recession probability of common transitory component



(a) Filtered probability (b) Smoothed probability

Our results may be compared to those reported in Mills and Wang (2002a), where a model with just a common factor is used, without decomposing the factor into its permanent and transitory components. This simpler model produced estimated average durations of expansion and recession of 18.4 and 5.6 quarters respectively. The recessionary duration estimate is thus close to those found here, but the expansionary duration is considerably smaller, by between a year to eighteen months depending on whether the comparison is with the permanent or transitory business cycle components. The factor loadings estimated in Mills and Wang (2002a) were of the same rank order as those for the common transitory component, but rather different from those for the common permanent component. The smoothed recession probabilities reported in Mills and Wang (2002a) show the three major recessions identified here, but obviously cannot distinguish whether they were primarily a consequence of permanent or transitory influences. The model fitted here is clearly statistically superior to the simpler model, since three of the factor loadings on the transitory component are significantly different from zero and the estimate of the 'plucking' parameter π is significantly negative.

We thus conclude that separating the common factor into permanent and transitory components provides a richer explanation of business cycle fluctuations in the UK. The average durations of expansions caused by permanent and transitory factors are estimated to be rather longer than if these are not separated out, factor loadings are different for the permanent component, and the recession of the mid-1970s is related to the transitory component of the business cycle, while the two later recessions are related to permanent factors. This all suggests that the features of each recession are different, so that, for example, a high-recovery phase is not always found to follow a recession, which is also confirmed by Kim and Murray (2002) for the US.

4. Conclusions

In this study we have applied Kim and Murray's (2002) multivariate Markov chain business cycle factor model to quarterly UK data for the last four decades, and found that the model captures the important features of the UK business cycle fairly well. The common permanent component, interpreted as a composite indicator of coincident variables, switches between regimes of boom and slump. On the other hand, the estimated common transitory component supports the peak-reversion behaviour of the business cycle movement and is particularly influenced by retail sales.

In addition, we also found significant timing differences between permanent and transitory components of recessions, notably the lack of the usual high-growth recovery phase following the early 1990s recession. Our results thus suggest that each recession is indeed different.

Endnotes

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2. Estimation was performed using routines written in GAUSS. No constraint was placed on the sign of π.

3. Except for the retail sales series, taken from Datastream, all other data are from the Office of National Statistics. The series codes are YBHH, NRJR, UKRETTOTG and BCAJ, respectively. We also tried workforce rather than employees, producing results similar to those reported here.

4. Results are available upon request.

5. The details of how to obtain the levels of the common permanent component are described in Stock and Watson (1991).

6.The chronology is presented as Table D1 of Artis, Kontolemis and Osborn (1997).

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