THE DECLINE IN THE VOLATILITY OF THE BUSINESS CYCLES IN THE UK

by

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We analyse the sources of the decline of business cycle volatility in the UK using a dynamic factor model that allows for the presence of a structural break in the conditional mean and variance of output, sales, income and unemployment. We augment the factor model with an economic component to investigate the role of structural changes and improved monetary policy in the volatility decline of the series. Our results suggest that the dominant cause for the observed volatility decline is the reduced variability of shocks.

1 Introduction

Recent empirical evidence suggests that business cycle fluctuations in the USA have dampened considerably over the last two decades, the so-called volatility moderation. Kim and Nelson (1999a) and McConnel and Perez-Quiros (2000) report a substantial reduction in the volatility of US output growth in the early 1980s. Chauvet and Potter (2001) and Ahmed et al. (2001) document evidence that this reduction in volatility is shared by other important macroeconomic variables such as employment, consumption and income.

Corresponding volatility reductions have been observed in other countries. Mills and Wang (2000), Blanchard and Simon (2001) and Smith and Summers (2002) examine the volatility of output growth in the G7 countries and find that all seven economies have experienced a decline in output growth volatility, although the magnitudes and dates of the breaks differ across countries. Stock and Watson (2002) examine industrial production of the G7 countries and also document the presence of breaks in volatility. Finally, van Dijk et al. (2002) provide evidence for a decline in volatility across a wide range of macroeconomic time series from each of the G7 countries.

* We thank the participants of the Money, Macroeconomics and Finance (MMF) Conference 2007, Karim Abadir, Peter N. Smith and Rob Hudson for their valuable suggestions. We are also grateful to S. Radchenko for making his estimation code available to us.
A focus of recent research has been to investigate the possible causes for the observed volatility decline. Three explanations are most common in this growing literature: structural change, improved macroeconomic policies and plain good luck. Most of the research, however, focuses on the US economy. In this paper, we estimate a factor model of UK real activity and investigate the role of the permanent and transitory factors in the volatility decline. It is informative to consider the UK case because of the extreme turbulence that characterized the UK economy in the past. Double-digit inflation alongside a recession was last experienced in the UK in the 1990s compared with 1980s for the USA. The inflation peaks of the mid-1970s and 1980s in the UK were almost double the corresponding peaks in the USA. During the 1970s monetary policy in the UK was considered ineffective for controlling inflation. Instead price controls were used and the policy makers did not let interest rates respond strongly to the take-off of inflation.

In the paper, we present formal inference about the timing of a possible common structural break in the mean and variance of output, sales, income and unemployment. We carry out tests to establish whether the changes in the estimates are large relative to what we might expect if no change had occurred. Our model allows for two sources of a possible break in the volatility of the permanent and transitory components. The first source is the change in the conditional variance of the components. The second source comes from the change in the size of the transitory and permanent shocks which is modelled as the break in the conditional mean of the process. Kim and Nelson (1999b) point out that an observed volatility reduction might be due to a shift either in the conditional mean or in the variance of the innovations.

In order to examine the role of the structural changes that have occurred in the last two decades or the improved effectiveness of monetary policy, we augment the model with a range of economic indicators. The economic variables we consider are various proxies for structural changes and measures of monetary policy effectiveness. We estimate the ratios of the conditional variances, for the period before the break and the period after the break, for the permanent, transitory and economic factors and analyse the relative importance of each factor in the decline of the conditional volatility.

The results show only weak evidence for volatility decline in the permanent factor. In contrast, there is strong evidence for reduced volatility of the transitory factor and the volatility of the shocks. The results from the three-factor model show that the inclusion of economic variables as proxies does not change significantly the estimates of either the permanent or the transitory components. We find that although the reduction in inflation volatility has contributed to the volatility moderation of real activity it does not appear to be a major factor driving the macroeconomic dynamics in the UK.
The remainder of this paper is organized as follows. Section 2 presents an overview of the related literature. Section 3 discusses some graphical evidence illustrating the major points of the study and considers the empirical specification we use. The inference about the possible structural changes in the properties of the series is presented in Section 4. In Section 5, we carry out variance decomposition analysis, present the estimation results from the factor model and investigate the sources of the observed volatility decline. Section 6 concludes the paper and outlines possible directions for future research.

2 Related Literature

A vast empirical literature attempts to explain the source of the dramatic decrease in the volatility of macroeconomic time series. The first explanation suggests that changes in economic institutions, technology, business practices and others have improved the responsiveness of the economy to exogenous shocks. For example, Kahn et al. (2002) argue that improvements in inventory management appear to be the main cause for the volatility moderation. Other sources of structural change include the increased depth and sophistication of financial markets, the shift away from manufacturing towards services, the increased openness and international capital flow.

The second explanation for the volatility moderation is consistent with Friedman’s (1977) hypothesis that increased inflation uncertainty may adversely affect real economic variables. In the last 15 years a significant number of central banks, including the Bank of England, adopted a policy of inflation targeting designed to ensure price stability. Since monetary policy has played a large part in stabilizing inflation in the last two decades and output volatility has declined in parallel with inflation volatility, many authors have suggested that improved monetary policy may be a cause for the decline in the variability of the macroeconomy.

The last explanation suggests that the reduction in the volatility of output growth is primarily accounted for by a reduction in the variance of macroeconomic shocks. Ahmed et al. (2001) and Stock and Watson (2003) find that the increased US macroeconomic stability can be attributed neither to ‘good business practice’ nor to ‘good policy’ but rather to ‘good luck’. The evidence in Benati and Surico (2006) also suggests an important role played by shocks in stabilizing the macroeconomic environment in the UK.

While the three possible explanations are not mutually exclusive, their relative importance has implications for future volatility since changes in the permanent and economic factors are likely to have a more permanent effect on volatility. A decline in the magnitude of shocks, on the other hand, may
only have a temporary effect. In other words, if improved monetary policy was the source of stability in the macroeconomy, the turbulence of the 1970s and 1980s would be a thing of the past. If, on the other hand, the UK economy has been spared by large shocks in the last two decades, monetary policy would not necessarily be effective at providing macroeconomic stability in the future.

A large number of studies have examined the effectiveness of monetary policy as a stabilization tool. Based on an estimated sticky-price model of the US economy, Lubik and Schorfheide (2004) find support for the good policy explanation, i.e. a shift in the systematic component of monetary policy has been the driving force behind the recent macroeconomic stability. Cecchetti et al. (2006) estimate movements towards an efficiency frontier for inflation and output variability and movements in the frontier itself. They also find that improved monetary policy accounts for most of the observed stability for a wide range of countries. In contrast, on the basis of structural vector autoregressive (VAR) analysis, the good luck hypothesis has been advocated by a number of authors including Stock and Watson (2002), Canova and Gambetti (2005), Primiceri (2005), Gambetti et al. (2006) and Sims and Zha (2006) for the USA, and by Benati and Surico (2006) for the USA, the Euro area and the UK.

There has been a debate in the literature about the empirical validity of these results and the empirical methodologies that have been used. Benati and Surico (2006) investigate the ability of VARs to identify the sources of the observed volatility decline. They point out that changes in the monetary policy rule have an impact on both the covariance matrix and the coefficients of the VAR representation of the model. In particular, the impact of the policy shift on the VAR covariance matrix can dominate the impact on the VAR coefficients. These changes in the volatilities of the VAR innovations have been interpreted as evidence against good policy and in favour of good luck. Second, changes in the interest rate equation of a structural VAR bear no clear-cut relationship with changes in the parameters of the monetary policy rule. Many studies have performed counterfactual simulations in structural VARs under the presumption that switching the estimated coefficients of the interest rate equations provides a reasonable approximation to switching the parameters of the monetary policy rule.

We use a dynamic multivariate factor model with regime switching and focus on the role played by the permanent and transitory factors in the volatility moderation in the UK. Diebold and Rudebusch (1996) argue that dynamic co-movements among macroeconomic variables are often well described by a particular configuration of the VAR associated with factor structure. Many empirical studies have analysed the nature of business cycle fluctuations using a factor model with regime switching. Hamilton (1989) and McConnel and Perez-Quiros (2000) model fluctuations as...
movements in the permanent stochastic trend. Kim and Murray (2002) extend their work and develop a multivariate model, which encompasses both the possibility of fluctuations around a permanent stochastic trend and Friendmand’s plucking hypothesis that large negative movements in the transitory component cause output to deviate from its trend. They measure the importance of the permanent and transitory component in explaining business cycle fluctuations and argue that only the transitory component plays an important part in explaining common fluctuations of the US macroeconomic series. In the context of this research agenda, Chauvet and Potter (2001) use a one-factor model to investigate a possible link between the reduction in volatility of the economic time series and the dynamics of the business cycle. Korenok and Radchenko (2006) introduce an exogenous time break in their factor model in order to analyse the possible causes for the observed volatility decline in the US real activity. Their results suggest that a significant part of the moderation of the business cycle is due to the moderation of transitory and idiosyncratic shocks.

3 Empirical Specification

3.1 Descriptive Evidence

Over the last several decades, the UK has moved from a situation in which inflation was controlled using non-monetary policies to one in which monetary policy directly targets inflation. Since the role of monetary policy in controlling inflation changed, the macroeconomic environment in the UK has been characterized by low volatility. Figure 1 shows the standard deviation, computed from a five-year (20-quarter) window, for the real GDP growth, sales, income and unemployment series for the UK covering the period 1971Q1–2005Q2. The reduction in the standard deviation of all series over the last two decades is clear.

Figure 1 also shows the estimated recession periods for the UK. Our graphical evidence should serve to remind us that recessions and expansions are indeed different. The figures suggest that recessions are times of higher output volatility than economic expansions. Therefore, not only should our empirical specification take into account breaks in mean and volatility but it should also account for asymmetries in the business cycle.

1 The data are obtained from Datastream and are transformed into annualized growth series. We follow Benati and Surico (2006) who also uses data from the beginning of the 1970s.

2 We use the dates estimated by Birchenhall et al. (2001).
3.2 Econometric Modelling

Consider the following unobserved factor model of economic fluctuations in which each individual time series \( y_{it} \) for \( i = 1, \ldots, N \) is decomposed into

\[
\begin{align*}
y_{it} &= \gamma_i c_t + \nu_{it} + \lambda_i x_t + \omega_{it} \quad t = 1, 2, \ldots, T
\end{align*}
\]  

(1)

where \( c_t \) is a permanent factor with idiosyncratic error term \( \nu_{it} \) and \( x_t \) is a transitory factor with error term \( \omega_{it} \). \( \gamma = [\gamma_1, \ldots, \gamma_N] \) and \( \lambda = [\lambda_1, \ldots, \lambda_N] \) are the factor loadings.

We transform all variables in first differences in order to handle the integration problem. The reduced-form model for output growth, sales, income and unemployment can be written as follows:

\[
\begin{align*}
\Delta y_{it} &= \gamma_i \Delta c_t + \lambda_i \Delta x_t + \xi_{it} \\
\xi_{it} &= \psi_i \xi_{i,t-1} + e_{it}
\end{align*}
\]  

(2)  

(3)
where $i = 1, \ldots, 4$ and $e_t \sim N(0, \sigma_t^2)$. The assumption that the idiosyncratic factor $\xi_t$ follows an autoregressive process of order one is the same as in Kim and Murray (2002). They point out that results are not materially different when other lag lengths are used.

We use Hamilton’s (1989) regime-switching model for the permanent component.

$$\Delta c_t = \phi \Delta c_{t-1} + \mu_{c_t} + \nu_t$$

$$\mu_{c_t} = \mu_0 + \mu_{c_t} S_{1t}$$

In the model, $\mu_{c_t}$ determines the growth rate of the permanent component during expansions and $\mu_0 + \mu_{c_t}$ determines the growth of the permanent component during recession. $\phi$ is an autoregressive coefficient and $S_{1t}$ is a two-state Markov process equal to zero when the economy is in expansion and equal to one during contraction. $S_{1t}$ has a transition probability matrix

$$P = \begin{bmatrix} p_{11} & 1 - p_{22} \\ 1 - p_{11} & p_{22} \end{bmatrix}$$

and $\nu_t \sim N(0, \sigma_t^2)$.

The transitory component is modelled using a regime-switching version of Friedman’s (1964) model.

$$x_t = \phi x_{t-1} + \pi_{S_{2t}} + \eta_t$$

$$\pi_{S_{2t}} = \pi_{S_{2t}} S_{2t}$$

The transitory factor has zero mean during expansions and negative mean equal to $\pi_t$ during contractions, i.e. negative movements in the transitory component cause output to deviate from its trend. In equation (5), $\phi$ is an autoregressive parameter, $S_{2t}$ is a two-state Markov process equal to zero when the economy is in expansion and equal to one during contraction. $S_{2t}$ has a transition probability matrix

$$Q = \begin{bmatrix} q_{11} & 1 - q_{22} \\ 1 - q_{11} & q_{22} \end{bmatrix}$$

and $\eta_t \sim N(0, \sigma_t^2)$.

Next, we allow for a structural break in the dynamics of the permanent and transitory components. The model allows two sources of change in the volatility of the permanent and transitory components. The first source is the change in the conditional variance of the components. The second source comes from the change in size of the transitory shocks and size of the permanent shocks which is modelled as the break in conditional mean of the processes. We write the regime-dependent parameters of the model as follows:
\[ \mu_{0t} = \begin{cases} \mu_{01} & \text{if } t \leq T_{\text{break}} \\ \mu_{02} & \text{if } t > T_{\text{break}} \end{cases} \quad \mu_{1t} = \begin{cases} \mu_{11} & \text{if } t \leq T_{\text{break}} \\ \mu_{12} & \text{if } t > T_{\text{break}} \end{cases} \]

\[ \pi_t = \begin{cases} \pi_1 & \text{if } t \leq T_{\text{break}} \\ \pi_2 & \text{if } t > T_{\text{break}} \end{cases} \]

\[ \sigma_{01}^2 = \begin{cases} \sigma_{01}^2 & \text{if } t \leq T_{\text{break}} \\ \sigma_{02}^2 & \text{if } t > T_{\text{break}} \end{cases} \quad \sigma_{11}^2 = \begin{cases} \sigma_{11}^2 & \text{if } t \leq T_{\text{break}} \\ \sigma_{12}^2 & \text{if } t > T_{\text{break}} \end{cases} \]

where \( T_{\text{break}} \) is the date of the common structural break.

The model (2)–(5) is not identified so we follow the previous work in the area (see Korenok and Radchenko, 2006) and set the variances of the permanent and transitory components for the period before the volatility break to \( \sigma_{01}^2 = \sigma_{02}^2 = \frac{1}{2} \). These restrictions imply that

\[ \sigma_{01}^2 = \begin{cases} \frac{1}{2} & \text{if } t \leq T_{\text{break}} \\ \frac{\sigma_{02}^2}{2\sigma_{01}^2} & \text{if } t > T_{\text{break}} \end{cases} \quad \sigma_{11}^2 = \begin{cases} \frac{1}{2} & \text{if } t \leq T_{\text{break}} \\ \frac{\sigma_{12}^2}{2\sigma_{11}^2} & \text{if } t > T_{\text{break}} \end{cases} \]

### 4 Estimation and Structural Break Analysis

#### 4.1 Estimation Strategy

We estimate the state-space model with Markov switching using a modification of the Bayesian approach of Kim and Nelson (1998). Details of the state-space representation and the Gibbs sampling algorithm are presented in Appendix A and B to the paper. The prior distributions for the model parameters are presented in Table 1.

Let \( \Theta = [\gamma, \lambda, \delta, \psi, \mu_{01}, \mu_{02}, \mu_{11}, \mu_{12}, \pi_1, \pi_2, \Sigma, \phi, \rho, \sigma_{01}^2, \sigma_{11}^2, \sigma_{02}^2, \sigma_{12}^2, \Sigma_{\text{ij}}, p_{11}, p_{22}, q_{11}, q_{22}] \), where \( \Sigma = [\sigma_{11}, \ldots, \sigma_{n1}, \sigma_{12}, \ldots, \sigma_{n2}] \) and \( n = 4 \). In order to achieve identification we impose the prior restrictions \( \mu_{01} < 0, \mu_{11} < 0, \mu_{02} > 0, \mu_{12} > 0, \pi_1 < 0, \pi_2 < 0 \), and the prior distributions for the parameters \( \mu_0, \mu_1 \) and \( \pi \) are the same before and after the break. Also, we assume that the first difference of the permanent component and the level of the transitory component are covariance stationary processes \( |\phi| < 1 \) and \( |\phi| < 1 \). We set the values of the hyperparameters in the prior distributions equal to the estimates reported in the literature. The parameters \( \sigma_{ij}^2 (i = 1, \ldots, n \text{ and } j = 1, 2) \) have Jeffreys prior distributions and \( p_{ii}, q_{ii} (i = 1, 2) \) have Beta prior distributions with means \( E(p_{11}) = E(q_{11}) = 0 \) and \( E(p_{22}) = E(q_{22}) = 0.8 \). To estimate the model, we construct a chain of 2000 draws using a Gibbs sampler and discard the first 1000 to minimize the effect of the initial conditions.
4.2 Structural Break Tests

We estimate several factor models. First, we use a two-factor model with permanent and transitory factors with a volatility break as our benchmark (BM) model. Then we compare the results of this model with the results of the same model without a break. We model the change in variance formally in the spirit of McConnel and Perez-Quiros (2000) or Chauvet and Potter (2001) and estimate the model with the assumption that the break date is unknown. Thus we extend the analysis in Korenok and Radchenko (2006) since they assume that the break date is known.

We start by using a simple grid search procedure to estimate the break date \( \tau \). The idea is to calculate the likelihood ratio (LR) statistic for all possible structural breaks, given that \( \tau \in [\tau_l, \tau_H] \), where \( \tau_l = (1 - \pi)T \) and \( \tau_H = \pi T \) for some truncation parameter \( \pi \). Then the maximum LR value is the test statistic and the associated \( \tau \) is the estimated change point. We obtain \( \hat{\tau} = 1988Q4 \).

Sequential break point tests are a good starting point. They are useful at selecting a possible time interval within which the actual break may be found. However, these tests may fail to produce the correct critical values. The test statistics derived do not have standard distributions and the correct critical values should be simulated via Monte Carlo methods (see Hansen, 2000). Therefore, we turn to Qu and Perron’s (2005) methodology for estimation and inference in a system of equations with multiple structural changes occurring at unknown dates. In this procedure, changes can occur in the parameters of the conditional mean and the covariance matrix of the errors.

Given the size of our sample we set \( \pi = 35 \) per cent.

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The method allows for conditional heteroskedasticity, autocorrelation and for arbitrary restrictions on the parameters of the system. The latter permits the analysis of common breaks for all series as well as breaks occurring only in a subset of equations. Qu and Perron show that substantial efficiency gains can be obtained by casting a regression affected by changes in a system of equations even if the other equations are not affected by the break.

We assume that the time-series processes can be adequately approximated by a VAR model where all the parameters are allowed to break at a fixed number of dates. We allow for a maximum of two possible breaks in the conditional mean and the covariance matrix of the errors. The sequential testing procedure rejects the hypothesis of two breaks in favour of one structural break. Table 2 also reports confidence intervals (CI) for the break date. Many papers have now documented the volatility decline in the USA starting in the mid-1980s, although there has been some debate over whether the decline has been smooth or a one-off shift, as well as potential causes of the decline. Previous studies, however, find no apparent break in the mean growth of GDP despite the much discussed productivity slowdown in the 1980s and the information technology bubble in the 1990s. We compare a model where both the conditional mean and variance are allowed to break with a model where structural breaks can only occur in the covariance matrix of the errors and not in the mean. Table 2 shows that the restricted model with constant mean is not preferred relative to the unrestricted model. Therefore, unlike the evidence for the USA, the evidence for the UK suggests the presence of a structural break in the conditional mean of the series.

### Table 2

<table>
<thead>
<tr>
<th>Test statistics</th>
<th>Significance level at 1 per cent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sequential test for 2 versus 1 break</td>
<td>32.156</td>
</tr>
<tr>
<td>WDmaxLR test for up to 2 breaks</td>
<td>32.977</td>
</tr>
<tr>
<td>SupLR for 0 versus 1 break</td>
<td>49.555</td>
</tr>
<tr>
<td>SupLR for 0 versus 2 breaks</td>
<td>31.602</td>
</tr>
<tr>
<td>First break</td>
<td>(90% CI) 1983Q2–1985Q1</td>
</tr>
<tr>
<td>Second break</td>
<td>(90% CI) 1989Q3–1991Q3</td>
</tr>
<tr>
<td>Sequential test for 1 versus 0 breaks</td>
<td>94.898</td>
</tr>
<tr>
<td>WDmaxLR test for up to 1 break</td>
<td>32.977</td>
</tr>
<tr>
<td>SupLR for 0 versus 1 break</td>
<td>31.602</td>
</tr>
<tr>
<td>Single break</td>
<td>(90% CI) 1985Q1–1987Q4</td>
</tr>
<tr>
<td>Information criteria</td>
<td>AIC</td>
</tr>
<tr>
<td>Model with constant mean</td>
<td>7.323</td>
</tr>
<tr>
<td>Unrestricted model</td>
<td>11.916</td>
</tr>
</tbody>
</table>

Note: WDmaxLR test applies weights to the individual tests such that the marginal p values are equal across values of m (number of breaks). AIC, Akaike information criterion; BIC, Bayesian information criterion.
The rest of the analysis assumes that the break date is 1987Q3. Table 3 documents the average and the standard deviation of the quarterly growth rates for each series across subsamples—before and after the break. The summary statistics provide further support for the results from the structural break analysis. We observe a marked decline in the volatility of all series after the break and these differences are significant at conventional levels.

5 Sources of Volatility Decline

5.1 Economic Factor

In this section, we add an economic factor and estimate several different three-factor models to analyse the relationship between the economic factors and the common permanent and transitory factors. Equation (1) becomes

$$y_{it} = \gamma_i c_t + v_{it} + \lambda_i x_i + \omega_{it} + \delta_i z_t$$

(8)

where $z_t$ is a common economic factor and $\delta_i$ is the factor loading for the $i$th series.

We argue that, if the common economic factor $z_t$ has a non-trivial effect on the fluctuations of the UK real economic activity, then this effect will be captured either by the permanent or by the temporary factors. Therefore, when we introduce the economic factor in the model, the estimates for the loadings of the permanent and transitory factors and the variance decomposition (discussed below) in the three-factor model will be affected. If the estimates of the three-factor model are not significantly different from the estimates of the two-factor model, the economic factor $z_t$ does not play an important role in the business cycle dynamics and volatility moderation. Kose et al. (2003) and Korenok and Radchenko (2006) adopt a similar approach. Kose et al. introduce German investment growth as a second-world factor in their model and estimate how this additional factor changes the initial estimate of the first-world factor. Korenok and Radchenko investigate the effect of oil price changes, interest rates and stock returns on the fluctuations of the US economy in a multivariate factor model.

Table 3

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Volatility</td>
<td>Mean</td>
</tr>
<tr>
<td>Output</td>
<td>2.25</td>
<td>5.13</td>
<td>2.40</td>
</tr>
<tr>
<td>Income</td>
<td>2.78</td>
<td>7.89</td>
<td>2.89</td>
</tr>
<tr>
<td>Sales</td>
<td>2.50</td>
<td>7.08</td>
<td>3.18</td>
</tr>
<tr>
<td>Unemployment</td>
<td>9.66</td>
<td>25.52</td>
<td>6.54</td>
</tr>
</tbody>
</table>

4Using 1988Q4 as a break date does not change the main results of the paper.
We consider economic variables, which measure the impact of the changes in the monetary policy on macroeconomic stability. Romer (1999) and Blanchard and Simon (2001) find that monetary policy has a large contribution to stabilizing economic downturns. Nelson and Nikolov (2002) find evidence that monetary policy of inflation targeting can deliver stable inflation even in the face of very large shocks. In addition, a number of papers have established a close link between the decline in inflation volatility and output volatility. We use inflation volatility as an indirect measure of monetary policy effectiveness.\(^5\) However due to endogeneity (inflation volatility and output volatility are likely to be hit by common shocks) it is difficult to interpret the link between the two in a causal sense. We need a more direct measure of changes in monetary policy regimes that is not likely to be affected by output volatility. Most of the post-war recessions in the G7 countries were preceded by rising interest rates. Therefore, we analyse an alternative specification of the economic factor—the lagged value of short-term interest rates.\(^6\)

Next we investigate the role of structural changes in the stabilization of the UK real economy. The expansion of international trade in the last two decades has entailed integration into larger, deeper, more stable markets, which has promoted risk diversification and stability. Empirical evidence based on measures of international integration and financial system’s depth is mixed. Barell and Gottaschalk (2004) find that greater openness to trade and deeper financial systems are associated with lower volatility, while Buch et al. (2002) find no relationship. We consider trade openness and the ratio of credit to GDP.

In addition, it is possible that firms have become more adept at managing demand shocks and this has resulted in reducing volatility of output. Advances in information technology have helped firms improve their inventory management. Kahn et al. (2002) argue that the clear-cut downward trend in the US inventory-to-sales ratio from the mid-1980s is attributable to improved inventory management techniques. While supply-side factors may have played a role in the declining volatility of inventories, changes in the nature of demand may have also played a role. For example, more stable consumption would facilitate a reduction in the inventory-to-sales ratio and reduce the volatility of inventories. Similarly, the shift away from the more volatile manufacturing sector and towards the service sector has been suggested as an explanation (Dalsgaard et al., 2002). Blanchard and Simon (2001) find that such changes in the composition have not played an important role in the decline of output volatility. For these reasons and the fact that

\(^5\)We calculate the volatility of inflation using a rolling standard deviation procedure. The results of the paper are not materially different if we use the conditional volatility of inflation derived from a generalized autoregressive conditional heteroskedasticity (GARCH) model.

\(^6\)We use the three-month inter-bank interest rate.
data limitations make it difficult to remove the effect of changes in inventories from GDP we do not deal with these possibilities in this paper.

5.2 Variance Decomposition and Interpretation of the Results

In order to evaluate the importance of the different factors in explaining volatility moderation of the UK business cycle we use a measure proposed by Kim and Murray (2002). The variance of \( \Delta y_t \) can be written as follows:

\[
\text{var} (\Delta y_t) = \gamma^2 \text{var} (\Delta c_t) + \lambda^2 \text{var} (\Delta x_t) + \delta^2 \text{var} (\Delta z_t) + 2 \delta \gamma \text{cov} (\Delta c_t, \Delta z_t) + 2 \delta \lambda \text{cov} (\Delta x_t, \Delta z_t) + \text{var} (\xi_t)
\]  

(9)

Using equation (9) we can decompose the variance of the observed variables in the system into the variance attributed to the permanent factor, the variance attributed to the transitory factor, the variance attributed to the economic factor and the variance attributed to the idiosyncratic shock. It is possible to quantify the role each component played in the volatility moderation of each series for the period before the break date and after the break date.

Disregarding the effects of the covariances of the common factors with the economic factor, the volatility change across the two periods can be written as

\[
\frac{\gamma^2 \text{var} (\Delta c_t)}{\text{var} (\Delta y_t)} + \frac{\lambda^2 \text{var} (\Delta x_t)}{\text{var} (\Delta y_t)} + \frac{\delta^2 \text{var} (\Delta z_t)}{\text{var} (\Delta y_t)} + \frac{\text{var} (\xi_t)}{\text{var} (\Delta y_t)} \approx 1
\]

where

\[
\Delta \text{var} (\Delta y_t) = \text{var} (\Delta y_{it, t \geq \text{break} }) - \text{var} (\Delta y_{it, t < \text{break} })
\]

\[
\Delta \text{var} (\Delta c_t) = \text{var} (\Delta c_{it, t \geq \text{break} }) - \text{var} (\Delta c_{it, t < \text{break} })
\]

\[
\Delta \text{var} (\Delta x_t) = \text{var} (\Delta x_{it, t \geq \text{break} }) - \text{var} (\Delta x_{it, t < \text{break} })
\]

\[
\Delta \text{var} (\Delta z_t) = \text{var} (\Delta z_{it, t \geq \text{break} }) - \text{var} (\Delta z_{it, t < \text{break} })
\]

\[
\Delta \text{var} (\xi_t) = \text{var} (\xi_{it, t \geq \text{break} }) - \text{var} (\xi_{it, t < \text{break} })
\]

5.3 Estimation Results

Table 4 reports the estimated parameters of the BM two-factor model and the three-factor models. Panel B reports the estimates for the regime-dependent parameters. There is strong evidence of a break in the conditional mean of the transitory component. It increases from \( \pi_1 = -8.946 \) (during contractions) before the break to \( \pi_2 = -1.474 \) (during contractions) after the break. The estimates for the two periods are significantly different at all conventional levels. In contrast, we cannot reject the hypothesis of a constant conditional
The mean of the permanent component before and after the break. The size of the conditional mean of the permanent factor during expansion decreases from $m_{01} = 1.147$ to $m_{02} = 0.829$ and increases from $m_{11} = -1.416$ to $m_{12} = -0.901$ during contractions but the difference is not statistically significant.

The results from the three-factor models can be summarized as follows. The results in Table 4 show that the additional factors do not change significantly the estimated coefficients of the permanent and transitory components. It is possible that the lack of correlation between the transitory component and the economic factors is present because transitory shocks

<table>
<thead>
<tr>
<th>Panel A: Transition probabilities</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_{11}$</td>
</tr>
<tr>
<td>$p_{22}$</td>
</tr>
<tr>
<td>$q_{11}$</td>
</tr>
<tr>
<td>$q_{22}$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Regime-dependent parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_{01}$</td>
</tr>
<tr>
<td>$\mu_{11}$</td>
</tr>
<tr>
<td>$\mu_{02}$</td>
</tr>
<tr>
<td>$\mu_{12}$</td>
</tr>
<tr>
<td>$\pi_{1}$</td>
</tr>
<tr>
<td>$\pi_{2}$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: Permanent factor loadings</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_{1}$</td>
</tr>
<tr>
<td>$\gamma_{2}$</td>
</tr>
<tr>
<td>$\gamma_{3}$</td>
</tr>
<tr>
<td>$\gamma_{4}$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel D: Transitory factor loadings</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_{1}$</td>
</tr>
<tr>
<td>$\lambda_{2}$</td>
</tr>
<tr>
<td>$\lambda_{3}$</td>
</tr>
<tr>
<td>$\lambda_{4}$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel E: Autoregressive parameter for the common component</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\phi$</td>
</tr>
<tr>
<td>$\phi^{*}$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel F: Autoregressive parameter for the idiosyncratic component</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\psi_{1}$</td>
</tr>
<tr>
<td>$\psi_{2}$</td>
</tr>
<tr>
<td>$\psi_{3}$</td>
</tr>
<tr>
<td>$\psi_{4}$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel G: Third factor loadings</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta_{1}$</td>
</tr>
<tr>
<td>$\delta_{2}$</td>
</tr>
<tr>
<td>$\delta_{3}$</td>
</tr>
<tr>
<td>$\delta_{4}$</td>
</tr>
</tbody>
</table>

Notes: $^{a}$Interest rate for panels A and B; base rate for panels C–F.
Standard errors are reported in parenthesis.
have different origins and therefore cannot be explained by a single observable economic variable.

All factor loadings have the correct sign. The loadings for credit-to-GDP ratio are not significant for any of the data series, whereas the loadings for trade-to-GDP ratio are significant for all series. Inflation volatility and the lag short-term interest rate have significant factor loadings for output and income growth but are not significant for sales and unemployment.

Table 5 reports the estimates of the conditional variance for the BM model and the four different specifications of the three-factor model. Panel A reports the estimates for the period before the break, whereas panel B reports the estimates for the period after the break. The decline in the conditional variance of the transitory factor across the two periods is large and goes from var(\(D_{xt}\)) = 22.38 to var(\(D_{xt}\)) = 1.08. The relative decline of the variance of the permanent factor is much smaller (from var(\(D_{ct}\)) = 5.31 to var(\(D_{ct}\)) = 3.22).

<table>
<thead>
<tr>
<th>Panel A: 1971Q1–1987Q3</th>
<th>(\sigma_{\Delta xt}^2)</th>
<th>(\sigma_{\Delta ct}^2)</th>
<th>(\sigma_t^2)</th>
<th>(\sigma_1^2)</th>
<th>(\sigma_2^2)</th>
<th>(\sigma_3^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BM</td>
<td>5.31</td>
<td>22.38</td>
<td>14.92</td>
<td>44.80</td>
<td>31.70</td>
<td>221.25</td>
</tr>
<tr>
<td>Inflation volatility</td>
<td>1.20</td>
<td>20.35</td>
<td>14.97</td>
<td>43.32</td>
<td>26.83</td>
<td>229.33</td>
</tr>
<tr>
<td>Credit/GDP</td>
<td>5.09</td>
<td>20.84</td>
<td>15.89</td>
<td>47.33</td>
<td>28.78</td>
<td>220.34</td>
</tr>
<tr>
<td>Trade/GDP</td>
<td>3.02</td>
<td>20.98</td>
<td>14.42</td>
<td>46.55</td>
<td>30.74</td>
<td>203.70</td>
</tr>
<tr>
<td>Base rate</td>
<td>3.41</td>
<td>13.30</td>
<td>20.81</td>
<td>51.40</td>
<td>30.59</td>
<td>220.36</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: 1987Q4–2005Q2</th>
<th>(\sigma_{\Delta xt}^2)</th>
<th>(\sigma_{\Delta ct}^2)</th>
<th>(\sigma_t^2)</th>
<th>(\sigma_1^2)</th>
<th>(\sigma_2^2)</th>
<th>(\sigma_3^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BM</td>
<td>3.22</td>
<td>1.08</td>
<td>1.66</td>
<td>21.78</td>
<td>5.67</td>
<td>47.37</td>
</tr>
<tr>
<td>Inflation volatility</td>
<td>1.34</td>
<td>0.93</td>
<td>1.50</td>
<td>21.29</td>
<td>5.91</td>
<td>47.85</td>
</tr>
<tr>
<td>Credit/GDP</td>
<td>2.23</td>
<td>3.10</td>
<td>1.28</td>
<td>21.35</td>
<td>4.83</td>
<td>47.75</td>
</tr>
<tr>
<td>Trade/GDP</td>
<td>0.72</td>
<td>2.97</td>
<td>1.23</td>
<td>20.16</td>
<td>6.02</td>
<td>45.67</td>
</tr>
<tr>
<td>Base rate</td>
<td>0.92</td>
<td>7.67</td>
<td>1.45</td>
<td>20.71</td>
<td>3.97</td>
<td>47.44</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: Test for differences in variances: 1971Q1–2005Q2</th>
</tr>
</thead>
<tbody>
<tr>
<td>(t_v)</td>
</tr>
</tbody>
</table>

Critical values for \(\chi^2(1)\) at 1 per cent

\[ t_v = \frac{N \times [\hat{\sigma}^2(2) - \hat{\sigma}^2(1)]^2}{2 \times [\hat{\sigma}^2(2) + \hat{\sigma}^2(1)]} \]

asymptotically \(\chi^2(1)\).

\[ N = 137 \text{ and under } H_0 \]
Formal tests for differences in variances are reported in panel C of Table 5. The changes in the dynamics of the permanent and transitory factors are shown in Fig. 2.

The results in Table 5 provide strong evidence for a break in the variance of the idiosyncratic shocks. There is a large reduction in the idiosyncratic variances for all series after the break. Overall our evidence is in line with the evidence in Korenok and Radchenko (2006) for the USA and the evidence in Benati and Surico (2006) for the UK that good luck has played an important role in stabilizing real economic activity.

Next we turn to variance decomposition analysis. Panel A of Table 6 presents the relative contribution of the factors to the variance of the series in the system. The results show that the role played by the permanent and
transitory components has changed across the two periods. The transitory component explains from 6.33 per cent of total variation for unemployment to 50.09 per cent of total variation for GDP before the break. The significance of the transitory component declines after the break and it explains from 1 per cent of variation for unemployment to 34.28 per cent of variation for GDP. The contribution of the permanent factor has moved in the opposite direction after the break. It has increased from a range of 0.30–4.97 per cent to a range of 1–28.30 per cent. The evidence regarding the idiosyncratic component is mixed. The share of the idiosyncratic component has declined for GDP and sales but it has increased for income and unemployment.

Panel B of Table 6 reports the decomposition of the volatility decline for each series for the BM model. According to the results the decline in the volatility of the transitory component explains from 8.13 per cent to 51.05 per cent of the reduction in volatility of the variables in the system. Moderation in the volatility of the permanent component is small, 0.19–2.17 per cent. The relatively larger reduction in the volatility of the transitory factor explains the previous finding that after the break the permanent component becomes more important relative to the transitory component. Another important result from Table 6 concerns the role of the variance of the idiosyncratic shocks in the volatility moderation of the series. For income and unemployment the decline in the variance of the idiosyncratic component explains more than 90 per cent of the decline of the volatility of the series.

Tables 7–10 contain the results from the variance decomposition analysis for the three-factor models. The results show that all of the economic factors appear to contribute to the decline of the total variance of the data series but contributions are generally small. The most important ones are the

\begin{table}
\centering
\caption{Variance Decomposition Analysis for the BM Model (1971Q1–2005Q2)}
\begin{tabular}{|l|c|c|c|c|}
\hline
\multicolumn{5}{|c|}{Percentage of total variance attributed to} \\
\multicolumn{5}{|c|}{Permanent component | Transitory component | Idiosyncratic component} \\
\hline
Panel A & & & & \\
\hline
GDP & 2.53 & 28.30 & 50.09 & 34.28 & 47.37 & 37.42 \\
Income & 1.02 & 2.47 & 25.31 & 3.76 & 73.66 & 93.77 \\
Sales & 4.97 & 18.16 & 12.67 & 2.84 & 82.36 & 79.00 \\
Unemployment & 0.30 & 1.00 & 6.33 & 1.00 & 93.28 & 98.01 \\
\hline
Panel B & & & & \\
\hline
GDP & 1.00 & 51.05 & & & 47.98 \\
Income & 0.50 & 33.06 & & & 66.44 \\
Sales & 2.17 & 14.75 & & & 83.07 \\
Unemployment & 0.19 & 8.13 & & & 91.68 \\
\hline
\end{tabular}
\end{table}

\begin{table}
\centering
\caption{Percentage of variance decline attributed to} \\
\multicolumn{5}{|c|}{Permanent component | Transitory component | Idiosyncratic component} \\
\hline
Panel A & & & & \\
\hline
GDP & 1.00 & & & & \\
Income & 0.50 & & & & \\
Sales & 2.17 & & & & \\
Unemployment & 0.19 & & & & \\
\hline
Panel B & & & & \\
\hline
GDP & 1.00 & & & & \\
Income & 0.50 & & & & \\
Sales & 2.17 & & & & \\
Unemployment & 0.19 & & & & \\
\hline
\end{tabular}
\end{table}

volatility of inflation and trade-to-GDP ratio. The percentage of total decline attributable to the volatility of inflation varies from 0.74 per cent to 7.33 per cent and the decline attributable to trade-to-GDP ratio varies from 0.97 per cent to 20.65 per cent. Overall, these results provide evidence that supports the conjecture that the reduced inflation and the greater openness in the economy have contributed to the decline of business cycle volatility in the UK. The evidence for the importance of the depth of financial markets is weaker.

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This paper developed a dynamic multivariate factor model to analyse the characteristics of the stochastic processes that underlie economic fluctuations in the UK. We estimate the timing of a structural break in the mean and variance of output, sales, income and unemployment. Introducing a break...

### Table 9
**Variance Decomposition Analysis for the Model with Trade-to-GDP Ratio (1971Q1–2005Q2)**

<table>
<thead>
<tr>
<th></th>
<th>Permanent</th>
<th>Transitory</th>
<th>Economic factor</th>
<th>Idiosyncratic</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP</td>
<td>6.13</td>
<td>17.74</td>
<td>11.20</td>
<td>10.59</td>
</tr>
<tr>
<td>Income</td>
<td>2.49</td>
<td>2.23</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Sales</td>
<td>6.21</td>
<td>10.39</td>
<td>19.69</td>
<td>10.76</td>
</tr>
<tr>
<td>Unemployment</td>
<td>1.67</td>
<td>2.27</td>
<td>4.77</td>
<td>0.12</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Percentage of total variance decline attributed to component</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP</td>
<td>4.58 11.28 3.13 78.86</td>
</tr>
<tr>
<td>Income</td>
<td>2.64 0.00 20.65 74.67</td>
</tr>
<tr>
<td>Sales</td>
<td>5.15 21.98 0.97 70.44</td>
</tr>
<tr>
<td>Unemployment</td>
<td>1.46 5.65 6.56 84.34</td>
</tr>
</tbody>
</table>

### Table 10
**Variance Decomposition Analysis for the Model with Lag Short-term Interest Rate (1971Q1–2005Q2)**

<table>
<thead>
<tr>
<th></th>
<th>Permanent</th>
<th>Transitory</th>
<th>Economic factor</th>
<th>Idiosyncratic</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP</td>
<td>9.28</td>
<td>27.04</td>
<td>14.40</td>
<td>42.63</td>
</tr>
<tr>
<td>Income</td>
<td>5.22</td>
<td>4.91</td>
<td>0.35</td>
<td>0.33</td>
</tr>
<tr>
<td>Sales</td>
<td>8.95</td>
<td>20.80</td>
<td>0.95</td>
<td>2.24</td>
</tr>
<tr>
<td>Unemployment</td>
<td>3.89</td>
<td>5.82</td>
<td>4.71</td>
<td>7.15</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Percentage of total variance decline attributed to component</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP</td>
<td>6.23 9.55 0.12 85.07</td>
</tr>
<tr>
<td>Income</td>
<td>5.50 0.36 0.37 93.42</td>
</tr>
<tr>
<td>Sales</td>
<td>6.28 0.66 2.66 89.24</td>
</tr>
<tr>
<td>Unemployment</td>
<td>3.13 3.73 2.75 93.30</td>
</tr>
</tbody>
</table>

6 Conclusions

This paper developed a dynamic multivariate factor model to analyse the characteristics of the stochastic processes that underlie economic fluctuations in the UK. We estimate the timing of a structural break in the mean and variance of output, sales, income and unemployment. Introducing a break...
into the factor model allows us to analyse the sources of the volatility decline by examining the changes in the permanent and transitory factors and the idiosyncratic shocks.

The results from the estimation of the factor model show that the transitory factor and the idiosyncratic shocks explain a significant part of the total volatility of the UK economic aggregates in the last two decades. When we augment the model with a third, economic factor, the results show that monetary policy effectiveness has contributed to the volatility decline of the real activity in the UK. This contribution, however, is small. Our results show that the dominant factor was the variability of macroeconomic shocks. However, we need to remember that what we have not done is to show causal links. Using reduced-form models does not allow for causal analysis. Determining the ultimate causes of the changes in volatility must be high on the agenda for future research.

APPENDIX A

Estimation of the Factor Model

We estimate model (1)–(6) in order to find a posterior distribution for the parameters of $\Theta$ and the unobserved state variables $c_t$, $x_t$, and $S_{1t}$ and $S_{2t}$. We use the Bayesian estimation procedure from Kim and Nelson’s (1998) state-space representation as our econometric model. The equivalent state-space representation of (1)–(6) is as follows:

$$\Delta y_t^* = H\zeta_t + \delta_t \Delta z_t^* + E_t$$  \hspace{1cm} (A1)

$$\zeta_t = \alpha_{S_1S_2} + F \zeta_{t-1} + V_t$$  \hspace{1cm} (A2)

$$E(U_tU_t') = Q$$  \hspace{1cm} (A3)

$$E(V_tV_t') = R$$  \hspace{1cm} (A4)

where $\Delta y_t^* = \Delta y_t - \psi_1 \Delta y_{t-1}$ and $\Delta z_t^* = \Delta z_t - \psi_1 \Delta z_{t-1}$ are $(n \times 1)$ vectors of the observed series, $E_t = [\xi_{1t}, \ldots, \xi_{kt}]'$, $\zeta_t$ is a $(k \times 1)$ state vector, $V_t$ is a $(k \times 1)$ vector of disturbances, $H$ is an $(n \times k)$ matrix of parameters and $F$ is a $(k \times k)$ matrix of parameters, $Q$ is an $(n \times n)$ diagonal covariance matrix of disturbances and $R$ is a $(k \times k)$ covariance matrix of disturbances. Also, using equations (A1)–(A4) we can derive the following definitions:

$$\zeta_t = \begin{bmatrix} c_t \\ x_t \\ c_{t-1} \\ x_{t-1} \\ c_{t-2} \\ x_{t-2} \end{bmatrix}, \quad \alpha_{S_1S_2} = \begin{bmatrix} \mu_{S_1} \\ \pi_{S_2} \end{bmatrix}, \quad V_t = \begin{bmatrix} v_t \\ u_t \\ 0 \\ 0 \end{bmatrix}$$

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Appendix B

Gibbs Sampling Algorithm

The hierarchical nature of the model allows us to use the Markov chain Monte Carlo integration method of Gibbs sampling to obtain the marginal posterior distributions for inference. We use the conditional densities derived in Kim and Nelson (1999b) and carry out the following steps.

1. Conditional on $\Theta$ and the state vectors $\{S_{1t}\}_{t=1}^{T}$, $\{S_{2t}\}_{t=1}^{T}$, we use the state-space model to generate the unobserved variables $\{\zeta_{t}\}_{t=1}^{T}$.
2. Conditional on $\Theta$ and $z_{t}$, we use the state-space model to generate the unobservable states $\{S_{1t}\}_{t=1}^{T}$ and $\{S_{2t}\}_{t=1}^{T}$.
3. Conditional on $z_{t}$, we use the state-space model to draw the parameters $\gamma_{i}$, $\lambda_{i}$, $\delta_{i}$ and $\sigma_{i}$ for $i = 1, 2, 3, 4$.
4. Conditional on $\{S_{1t}\}_{t=1}^{T}$, $\{S_{2t}\}_{t=1}^{T}$ and $\{\zeta_{t}\}_{t=1}^{T}$, we use the state-space model to generate $\mu_{0}$, $\mu_{1}$ and $\pi$.
5. Conditional on $\Theta$ and $\zeta_{t}$, we use the state-space model to generate $\psi_{i}$ for $i = 1, 2, 3, 4$.
6. Conditional on $\{S_{1t}\}_{t=1}^{T}$, $\{S_{2t}\}_{t=1}^{T}$, $\{\zeta_{t}\}_{t=1}^{T}$, $\mu_{0}$, $\mu_{1}$, $\pi$ and $\sigma_{u}^{2}/2\sigma_{v}^{2}$, we use the state-space model to generate $\phi$ and $\varphi$.
7. Conditional on $\{S_{1t}\}_{t=1}^{T}$, $\{S_{2t}\}_{t=1}^{T}$, we generate $p_{11}$, $p_{22}$, $q_{11}$ and $q_{22}$.

The above procedure is a straightforward extension of Albert and Chib’s (1993) Bayes inference via Gibbs sampling of autoregressive time series subject to mean and variance shifts. See Kim and Nelson (1999b) for details.

References


