AN ALTERNATIVE BUSINESS CYCLE DATING PROCEDURE FOR SOUTH AFRICA

ADÉL BOSCH* AND FRANZ RUCH†

Abstract
This paper applies a Markov switching model to the South African economy to provide an alternative classification of the business cycle. Principal components analysis (PCA) is used to determine the co-movement in the dataset to calculate the reference turning points over the period 1982 to 2009. Three complementary models are estimated using real gross domestic product (GDP), the composite coincident business cycle indicator data and the entire dataset used in the determination of the South African business cycle reference turning points. The research indicates that the models used generally coincide with the turning points published by the South African Reserve Bank (SARB), but that there are a few exceptions.

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* Corresponding author: Research Department, South African Reserve Bank, P O Box 3070, Pretoria, South Africa, 0001, tel. no.: +27 12 313 37-4242, fax no.: 012 313-4242, e-mail: Adel.Bosch@resbank.co.za

† Research Department, South African Reserve Bank, P O Box 3070, Pretoria, South Africa, 0001, tel. no.: +27 12 313-4420 , fax no.: 012 313-3925, e-mail: Franz.Ruch@resbank.co.za

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1. INTRODUCTION

The South African Reserve Bank (SARB) has been dating business cycle turning points since 1946 (Venter, 2009). SARB uses a combination of methods, closely following the Burns and Mitchell (1946) definition and Moore's (1980) approach.[1] It is, however, argued that the Burns–Mitchell and Moore approaches suffer from "measurement without theory" and lack "well-defined statistical properties" (Koopmans, 1947; Blanchard and Fischer, 1989). Banerji (2010) defends Moore's work and qualifies his defence by saying that Moore's process of identifying business cycle indicators was "rooted in business cycle theory: not falsifiable statistical models . . . but in a theoretical, conceptual understanding of the drivers of the business cycle, nevertheless". The aim of our paper is to determine an alternative methodology to dating business cycle turning points in South Africa, based on both "well-defined statistical properties" and a "firm understanding of the underlying drivers of business cycles. Accurate business cycle turning-point dates for an economy are crucial for policy-making and private sector decision-making. Accurate turning points allow policy-makers to implement countercyclical policy measures and provide the basis for comparing current data with historic phases. For the private sector, accurate business cycle turning points assist in arriving at informed sales and investment strategies.

This paper makes use of both a Markov switching model, similar to that used by Kontolemis (2001), and the Bry–Boschan (BB) algorithm (Bry and Boschan, 1971). This paper follows the growth rate cycle approach. Two other approaches that could be followed are (i) the growth cycle approach, that is, where data are de-trended, and deviations from trend are used to date upswings and downswings; and (ii) the classical cycles approach, where recessions and expansion are dated.

Our paper is the first attempt at using both a model-based approach and an algorithm to date the South African business cycle functionally. It differs from the available literature in three respects. First, unlike most of the literature that focuses on model estimation of the business cycle in quarterly terms (e.g., Moolman, 2004; du Plessis, 2006; Altug and Bildirici, 2010; Yadavalli, 2010), in this paper monthly data are used to ensure comparability with the current method adopted by SARB. Although monthly data posses certain challenges, this complementary method should provide policy-makers with more timely information regarding the state of the economy. Second, it is argued that gross domestic product (GDP) is not a sufficient measure of the business cycle and an attempt is made to provide further information regarding the state of the economy. To this end, principal components analysis (PCA) is employed on 123 variables of the 186 used in the official dating of the SARB business cycle, which allows for the uncovering of the correlation structure determining the aggregate business cycle. It was found that when using this method, business cycle turning points could be predicted more accurately than when using only GDP. Third, some model-based studies in the literature assume *a priori* that the SARB business cycle dates are correct (Moolman, 2003) and attempt to apply a model that predicts these dates using an indicator such as yield spreads and GDP. The Markov switching model uses a latent variable to model the regime shift and date the business cycle. This paper reveals that within the Markov switching framework, the mean and variance of each variable are sufficient estimators to determine accurate turning points in the South African economy, and no durational dependence or other dependent variables are necessarily required in the dating process. For the purposes of comparison, turning points are also identified using the BB algorithm.

This paper is set out as follows: in section 2 international literature on the dating of business cycles, particularly Markov switching models, and specifically their application in South Africa are considered. Section 3 is an outline of the methodological approach followed, including the Markov switching framework as described in Hamilton (1994), PCA and the BB method. Section 4 contains an elaboration of the data used in determining alternative business cycle turning points for South Africa. Section 5 presents the results, in which the Markov switching output is compared to SARB's reference

[1] For more detail on SARB's dating procedure, refer to Venter (2005).

turning points, the BB method, and to other studies. Section 6 contains the conclusion and suggestions for future work.

2. LITERATURE REVIEW

In terms of the fundamental (theoretical) understanding of business cycles, Burns and Mitchell (1946:3) defined business cycles as

> a type of fluctuation found in the aggregated economic activity of nations that organise their work mainly in business enterprises: a cycle consist of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of change is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own.

Moore (1980:4) stated that expansions and contractions should reflect an absolute rise and an absolute fall in trend-adjusted aggregate economic activity. It is important to note that expansions and contractions occur "at about the same time in many economic activities" and that no single index of economic activity can be seen to be superior to another (Moore, 1980:5). These contractions or expansions should last for at least six months, although there are no formal limitations on duration.

Similarly, a model-based approach to dating business cycles can be introduced. The application of Markov switching models to time series analysis began with the seminal work of Hamilton (1988; 1989). In the latter paper he formulated a nonlinear iterative filter that allowed for the maximum likelihood estimation of population parameters through a "discrete-valued unobserved state vector" (1989:358). He defined the algorithm as "formalising the statistical identification of 'turning points' of a time series" (1989:358).. He applied the method to his analysis of the business cycle in post-war United States (US) gross national product (GNP) and found that a shift from positive growth to negative growth was a recurrent feature in the data. He also found that the results were similar to the National Bureau of Economic Research (NBER) dating procedure and that this approach could be used as an alternative objective algorithm for dating. Much work has followed from this study, including that done by Phillips (1991); Goodwin (1993); Kim and Yoo (1995); Artis et al. (1997); Kim and Nelson (1999); Kontolemis (2001); Artis et al. (2004); and Altug and Bildirici (2010).[2]

Kontolemis (2001) used both univariate and multivariate Markov switching models, similar to Engel and Hamilton (1990), on the component variables of the US composite coincident indicator in order to determine the turning points of the business cycle. The variables used included the index of industrial production, non-agricultural employment, personal income (excluding transfer payments), and manufacturing and trade sales. The model was characterised by a mixture of two normal distributions, describing a low and high mean state, with switching between regimes governed by a Markov process. The author found that the resultant dating from a multivariate model was similar to the official NBER reference cycle and improved on univariate models of the component variables.

Altug and Bildirici (2010) used a univariate Markov regime switching model for GDP growth to characterise the business cycle of 22 developed and developing countries,[3] including South Africa. This cross-section allowed for the comparison of cyclical variation between developing and industrialised countries and the dating of individual business cycles. Their results were compared to other methods in order to determine the efficacy of the Markov switching model. They found evidence of a world factor that drove the cyclical fluctuations in both developed and developing countries, but there was also an important degree of heterogeneity among the countries studied. In the South African case evidence of non-linearity in GDP was found and that a two-regime Markov switching model best fitted the data spanning 1972 Q1 to 2009 Q1. The authors show that South Africa experienced the

[2] These works by no means constitute an extensive list.

[3] The other countries are Australia, Brazil, Canada, Chile, France, Hong Kong, Germany, Malaysia, Italy, Mexico, Japan, South Korea, the Netherlands, Singapore, Spain, UK, US, Taiwan, Turkey, Argentina and Uruguay.

smallest decline in output during contractions compared to other countries, but also low growth during expansions. The model also tracked the recessions over the sample period fairly well.

Research on non-linear models of the business cycle in South Africa is sparse and includes Moolman (2003; 2004); Botha (2004); and Altug and Bildirici (2010). Only Moolman (2004); and Altug and Bildirici (2010) employ a Markov switching model in their studies.

Moolman (2003) investigates the feasibility of looking at one indicator to predict turning points in the South African economy. The author uses a probit model to investigate the relationship between the turning points of the business cycle and several individual leading indicators. The results showed that based on goodness of fit, the short-term interest rate, with a lead of seven months, was most statistically significant; followed by SARB's composite leading indicator, which led by three months; and then the yield spread which had a lead of seven months. It was found that SARB's composite leading indicator gave two false signals over the period, while neither of the single variables gave false signals.

Moolman (2004) exploits the non-linear nature of the business cycle and forecasts turning points for the South African economy using both a Markov switching and logit model, and compares the results to that of a linear model. The yield spread is used as an explanatory variable in both models, similar to the research conducted by Nel (1996). The Markov switching model used by Moolman (2004) incorporates time-varying transition probabilities, which provide information on future movements of the business cycle. She follows Hamilton (1989) and makes use of an AR(4) two-regime Markov switching model. The data used are quarterly GDP and the yield spread is from 1978 to 2001. The Markov switching model outperformed both the linear AR(4) model and the logit model. The turning points and estimated probabilities of the Markov switching model closely match the SARB business cycle reference turning points. However, the Markov switching model signals an expansion in 1985 and a recession in 1994. These signals only last for one quarter and are therefore not dated based on the common cycle dating rule.[4]

Botha (2004) aims to construct a new leading indicator for the South African business cycle, and shows that changes in the business cycle are asymmetrical and should be modelled non-linearly. The non-linear models used in the analysis were, among others, various regime switching models. Botha found that the most popular measures to model the business cycle were the composite business cycle indicators and GDP. The regime switching models also outperformed the linear and neural network model.

Other methods and properties of the South African business cycle have been thoroughly explored in papers published by Frank (2001); du Plessis (2004); Boshoff (2005); Venter (2005); du Plessis (2006); du Plessis, Smit and Sturzenegger (2007); Venter (2009) and Yadavalli (2010). The most influential is the method used by SARB to date the reference turning points in the South African economy as described in Venter (2005) and again during the dating of the November 2007 upper turning point in Venter (2009).

Du Plessis (2006) uses a non-parametric dating algorithm (henceforth BBQ index**)** described by Harding and Pagan (2003), first suggested by Bry and Boschan (1971), to date turning points in the South African business cycle. However, this algorithm did not fit the South African GDP data well during the 1960s and the 1990s, as the economy experienced a prolonged expansion during both

[4] The common cycle dating rule defines 'a recession' as two consecutive quarters of negative GDP growth. Layton and Banerji (2003) question the origin of this common cycle dating rule, as some attribute the origin to Arthur Okun, although this reference is debatable. It is more likely that this rule originated from an article published in the *New York Times* in 1974 by Julius Shiskin (1974). He is often misquoted on what he refers to as a "quantitative definition of a recession" (Shiskin, 1974:222). In the article he defines a recession in terms of three dimensions (which should all be considered together): (i) duration, (ii) depth and (iii) diffusion. He is often only (incorrectly) quoted on duration, and hence the common cycle dating rule refers only to the duration of negative growth and considers GDP as the only variable.

periods. Du Plessis (2006) makes use of a transformed series by subtracting a deterministic linear trend, as opposed to the rate of change in GDP. The author implemented a concordance index, measuring the proportion of time that both the SARB coincident index and the BBQ index are either in an expansionary or contraction phase. The results show that the two indices are highly synchronised and significant. The main differences, however, include the fact that the average duration of contractions is shorter with the BBQ index than in the SARB index, whereas expansions have a similar average duration. The minimum duration of contractions is much shorter for the BBQ index. The SARB coincident index indicates relatively longer periods of contraction and shorter periods of expansion than the BBQ index. The BBQ index also records higher average growth during expansions and lower average growth during contractions.

One aspect of interest in our paper is the durational dependence of the business cycle discussed in Frank (2001) and du Plessis (2004). Frank (2001) makes use of a parametric Weibull Hazard function to test whether the South African business cycle is time-dependent, that is, whether the length of an expansion or recession has an impact on the probability of the economy switching states. The results showed that there is no evidence of time dependence in the South African business cycle, as the probability of a downward phase (upward phase) ending in South Africa does not rise the longer the duration of the upward phase (downward phase). Similarly, du Plessis (2004) makes use of non-parametric methods to investigate the duration dependence of the South African business cycle using the exponential distribution as the null hypothesis for three different tests. The business cycle is divided into two periods: (i) pre-1972 and (ii) post-1972. The results show that there is some evidence of duration-dependence in the pre-1972 down cycles, which is not so clear in the post-1972 down cycles. There is also weak evidence of duration dependence during the downward cycle and the total cycle in the post-1972 period. However, similar to what has been the case internationally, the South African business cycle does not display strong duration dependence to support even weak forms of periodicity.

3. METHODOLOGY

Following Hamilton (1994), the Markov switching model is characterised by a discrete time, discrete state Markov chain, a stochastic variable s_t with the Markov property, which determines the transition between states. The transition probabilities are:

$$P(s_t = j \mid s_{t-1} = i) = p_{ij} \tag{1}$$

with $(p_{ij})_{i,j=1,2}$ and $s_t = 1,2$ for time t. Two states are modelled in this paper to conform to the growth cycle contraction and expansion phase of the business cycle.[5] The Markov property ensures that the current state depends only on the previous state. The transition probabilities can be summarised in a transition matrix, P, for a two-state Markov chain as follows:

$$P = \begin{bmatrix} p_{11} & 1-p_{22} \\ 1-p_{11} & p_{22} \end{bmatrix} \tag{2}$$

The row j, column i element of P is the transition probability p_{ij}. For a more general representation of a Markov chain and the statistical properties, see Hamilton (1994).

The conditional density function of y_t, the observed variable, is:

$$f(y_t \mid s_t = j; \theta) = \frac{1}{\sqrt{2\pi\sigma_j}} \exp\left\{ \frac{-(y_t - \mu_j)^2}{2\sigma_j^2} \right\} \tag{3}$$

[5] Evidence of the appropriateness of two regimes is given in Altug and Bildirici (2010).

For j=1,2 and $\theta = (\mu_1, \mu_2, \sigma_1, \sigma_2, \rho_1, \rho_2)'$. The observed variable is assumed to be drawn from an $N(\mu_j, \sigma_j^2)$ distribution, subject to the specific state, which represents a mixture of two Gaussian distributions.[6] s_t is assumed to be generated by some probability distribution where the unconditional probability that it takes on value j is given by:

$$P(s_t = j; \theta) = \rho_j \tag{4}$$

Therefore, the joint density distribution function of y_t and s_t is equal to:

$$p(y_t, s_t = j; \theta) = f(y_t \mid s_t = j; \theta) P(s_t = j; \theta) \tag{5}$$

$$= \frac{\rho_j}{\sqrt{2\pi\sigma_j}} \exp\left\{ \frac{-(y_t - \mu_j)^2}{2\sigma_j^2} \right\} \tag{6}$$

Thus the unconditional density of y_t is:

$$f(y_t; \theta) = \sum_{j=1}^{2} p(y_t, s_t = j; \theta) \tag{7}$$

In order to get the maximum likelihood estimates of θ, the log-likelihood function of the observed data, $\ell(\theta) = \sum_{t=1}^{T} \log f(y_t; \theta)$ is maximised using the expectations–maximisation (EM) algorithm proposed in Hamilton (1989); this is due to the fact that the estimation is highly non-standard and requires the unobserved Markov chain s_t to be estimated. Hamilton (1994) states that the mixture density in equation 7 does not have a global maximum. However, Kiefer (1978) proved that the log-likelihood function has a bounded local maximum with consistent, asymptotically Gaussian estimates of the parameter coefficients.

Estimates in our paper are derived from a model with no autoregressive component, with only the mean and variance regime dependent similar to Engel and Hamilton (1990) and Kontolemis (2001). This is done for a number of reasons. First, results from Frank (2001) and du Plessis (2004) suggest that durational dependence is not present (or strong enough) to add autoregressive terms to the model structure in the South African context. Second, abstracting from the autoregressive parameters yields more appropriate results in determining the turning points. Third, since the variables used are coincident to the business cycle, we are only interested in the contemporaneous impact. Fourth, owing to the use of monthly data, the ability to maximise the EM algorithm given the necessary amount of autoregressive terms becomes computationally strenuous.

PCA is utilised in our paper in order to reduce the dimensionality of the coincident and diffusion data, but still ensuring that the majority of the variation in the dataset is present. This is particularly necessary, given the desire to model 123 variables in the diffusion context. According to Jolliffe (2005), this is achieved by creating a set of new variables, the principal components or factors, ordered such that the first few variables contain most of the variation and are uncorrelated across variables. The k^{th} principal component (PC) of a $k \times k$ vector of variables is $\alpha_k' x$ and $\text{var}(\alpha_k' x) = \lambda_k$ where λ_k is the k^{th} largest eigenvalue of the variance-covariance matrix, Σ, and α_k is the corresponding

[6] See Everitt and Hand (1981) and Titterington *et al.* (1985) for surveys on independent and identically distributed (i.i.d.) mixture distributions.

eigenvector.[7] Since the population variance-covariance matrix is unknown, it is replaced with a sample matrix, S. Generally, the PCs are derived subject to a normalisation restriction, $\alpha_k' \alpha_k = 1$.

In order to provide further comparison, the BB method for determining turning points in monthly series is applied[8]. The BB method makes use of an algorithm to determine turning points as established by the NBER. Table 1 describes the original BB monthly procedure (Bry and Boschan, 1971).

[Table 1 here]

4. DATA

The data used in our analysis were selected in such a way as to test whether one series sufficiently captures business cycle turning points. Following the three approaches followed in our paper, the first variable modelled was the change in the log of real GDP at market prices. The quarterly series was interpolated using linear trending and adjusting for seasonality in order to convert it into a monthly series. Next, the first PC extracted from the five indicators used in the SARB composite coincident business cycle indicator was tested. These indicators are summarised in Appendix A. Two factor models were then developed for the 186 series used in the SARB turning-point exercise. After visual inspection, some of the series were dropped due to their lack of cyclicality and starting date differences leaving 123 variables[9]. All the data were studied in log differences[10] and the period considered was 1982 to 2009. All data that were not available on a monthly basis were converted to a monthly frequency.

5. RESULTS

The Markov switching models are estimated in Gauss, using Bellone's (2005) Markov Switching Vector Autoregressive library (MSVARlib),[11] and the BB method in Scilab, using the Grocer package.[12] The GDP model serves as a benchmark model for this analysis and as a way to validate GDP as an appropriate aggregate measure in dating the business cycle. GDP is often used because it is seen as an estimate of aggregate economic activity. However, a composite coincident and diffusion index aims to capture the movement as the change in aggregate economic activity moves and spreads from one economic process to the next. By only looking at one indicator, GDP, these movements are typically lost. The coincident and diffusion indicators aim to provide a deeper understanding of the motions that are put in place when the economy changes from a recession (expansion) to an expansion (recession). This process is described in Banerji (2010) as a fall in income, leading to a fall in sales, followed by a fall in production and then in employment.

5.1 Gross Domestic Product Model

The GDP model infers that the 12-month growth rate in real GDP is subject to two regimes. Low regime periods are associated with lower or negative GDP growth, while high regime periods are associated with positive or high GDP growth. GDP is generally accepted as a good approximation of movements in the aggregate economy, although this may not necessarily mean that it accurately reflects the turning points of the business cycle as mentioned above. Other issues also exist. GDP is only available on a quarterly basis, while the coincident and diffusion index indicators are mostly available on a monthly basis. The GDP model uses linearly interpolated monthly data to test whether this would allow for adequate dating. GDP is also frequently revised, resulting in a change in the main indicator, while revisions in the coincident (diffusion) indicators do not make such a big difference in

[7] For a complete derivation of principal components analysis, see Jolliffe (2005).
[8] The BB algorithm is also adjusted, with a censoring rule, by Harding and Pagan (2003) to deal with quarterly data. This is referred to as the "BBQ algorithm".
[9] Variable list available on request.
[10] Capacity utilisation data were not transformed.
[11] For more information, see Bellone (2005).
[12] For more information, see Dubois and Michaux (2009).

the total coincident (diffusion) index. The BBQ method adopted by du Plessis (2006) is updated to test whether revisions to GDP do, in fact, make dating problematic. This model also provides information regarding the stylised facts of the South African business cycle which is lost when using PCA.

A mean–variance model (MSMH(2)-AR(0))[13] in which the mean and variance are regime-dependent was fitted. The results are presented in Table 2. μ_i and σ_i are the mean and variance respectively for regime i=1,2. Here, 1 is the downward phase and 2 is the upward phase. P_{11} is the probability that the current period is a downward phase, given that the previous period was a downward phase. The log-likelihood values, Bayesian Information Criterion (BIC) and the Jarque–Bera test statistic are also presented.

[Table 2 here]

Over the sample period, the average year-on-year growth rate during downward phases (regime 1) was a decline of 0,7 per cent, while the average growth rate during upward phases (regime 2) was 3,8 per cent. These estimates generally match Moolman (2004) and du Plessis (2006), who estimated a decline in the average growth rate during downward phases of 1,1 and 0,6 per cent and a 3,7 and 4,6 per cent increase in average growth during expansion periods. This, however, is in contrast to Altug and Bildirici (2010) who find the mean growth rate during the contraction phase to be 0,02 per cent and 2,06 per cent during expansions.[14] The average growth rate based on the SARB business cycle turning points were 0,3 per cent during downward phases and 3,6 per cent during upward phases. A possible reason why average growth is marginally positive during downward phases based on SARB's turning points, while average growth is negative based on the GDP model, can be attributed to the fact that some sectors in SARB's diffusion index only turn after GDP growth has already gained momentum. Finally, the BB method finds that growth averages 1,75 per cent during downward phases and 2,6 per cent during upward phases, differing substantially from all other results.

Similar to Altug and Bildirici (2010), the variance in growth in the GDP model is larger during contraction phases (0,023 per cent) compared to that during expansion phases (0,014 per cent). This result is expected, because, generally, downward phases during this period were exacerbated by large exogenous shocks, most significantly the financial crisis of 2007, but also the debt standstill agreement and isolation policies of the late 1980s.

Figure 1 plots the density of GDP growth in each regime over the sample period. The figure shows that GDP growth during a downward phase is more dispersed (i.e., has a larger base) compared to growth during an upward phase. During downward phases, growth can be anywhere between -4,6 and 2,1 per cent, while during upward phases, the spread is between 1,6 and 7,4 per cent. This implies that during downward phases, growth can remain positive, while growth during upward phases does not turn negative.

[Figure 1 here]

The transition probabilities show that over the sample period the average upward phase lasted just over 45 months, while the average downward phase lasted almost 29 months. Based on the SARB dating of the business cycle in South Africa since 1945, the average upward phase lasted close to 31 months (48 months for the sample period) and 20 months (35 months) in downward phases, excluding the current recession. The BB method applied to monthly GDP estimated an average upward phase of 18 months and an average downward phase of 20 months. The transition matrix also shows that the probability of the economy remaining in an upward phase given that the previous month was in an upward phase, is 97,7 per cent, while the probability of staying in a downward phase given that the previous month was also in a downward phase, is 96,5 per cent.

[13] Our paper follows the naming convention of Krolzig (1997).

[14] It is important to note the sample period differences between this paper and that of Altug and Bildirici (2010), and Moolman (2004). Altug and Bildirici (2010) studied the period 1972–2009, while Moolman (2004) studied the period 1978–2001.

Figure 2 plots the smoothed probabilities, those obtained from estimates of the probability that regime j occurs at time t given all available observations, for the GDP Markov switching model against the SARB turning points and the BB method. The area shaded in grey, where the business cycle takes on the value 1, represents the upward phases of the business cycle. The discrepancy between the model estimates and SARB's business cycle is 17,3 per cent. This discrepancy is relevant due to the desire to establish robust turning-point dates using a number of possible complementary methods. Overall, the model performs relatively well in dating the business cycle. However, as will be shown below, it is not as accurate as the composite coincident and diffusion models. One area of concern is the dating of the final downward phase of the South African economy during the late 2000s. According to the GDP model, the current recession only begins in November 2008, 11 months after the dating of SARB's reference turning points, 14 months later than the composite coincident MSMH(2)-AR(0) model and 17 months after the diffusion MSMH(2)-VAR(0) model. The late dating of the start of a recession is present in all four regime shifts in Figure 2. See Appendix B for the actual dating of each model.

[Figure 2 here]

For purposes of comparison, the BBQ methodology adopted in du Plessis (2006) is updated with the results provided in Appendix C. The updated dating procedure, which provides some positive evidence for the plausibility of GDP as a good approximation of the business cycle, does not differ significantly from the initial estimation undertaken in du Plessis (2006) even though the data has since been revised. The updated BBQ method differs from the initial estimation in two dates: (i) the start of the 1987 upward phase shifts to the fourth quarter from the first previously, and (ii) the 2004 upward phase begins in the fourth quarter of 2003 instead of the first quarter of 2004. This difference could also be attributed to the detrending technique. Canova (1999) and others have found that dating is sensitive to the type of detrending method applied. As more data are made available, the trendline no longer corresponds with the initial trendline calculated by du Plessis (2006) and therefore deviation from trend will differ. A more robust method, as applied is this paper, is to determine turning points in growth rate cycles. This method is, however, applied to quarterly data, whereas the SARB dating procedure is based on monthly data. To find an adequate comparison, the BB method is adopted on the monthly GDP data series and found to be substantially different to the other approaches in this paper. This method dates significantly more turning points.

5.2 Composite Coincident Model

The composite coincident model applies PCA to the five variables used in the composite coincident business cycle indicator, as calculated by SARB. The composite coincident data provides a starting point to consider more variables than just GDP and captures widespread movement in the economy, which will be lost if only a single variable were to be selected (Moore, 1980). Figure 3 plots the first PC from this analysis against the actual coincident business cycle indicator.[15] The cyclical pattern is clearly visible in this PC and it explains about 75 per cent of the co-movement in the five coincident indicator variables.

[Figure 3 here]

Table 3 presents the results of the composite coincident MSMH(2)-AR(0) model fitted to the first PC of the five subcomponents. Only the first PC is chosen for modelling after visual inspection of the Scree plot.[16]

[Table 3 here]

The transition probabilities show that over the sample period the average upward phase was just over 34 months (24 months based on the BB method), while the average downward phase was 28 months (19 months). Figure 4 plots the business cycle probability estimates of the composite coincident model

[15] To ensure compatibility the first principal component is inverted.

[16] A Scree plot is where the eigenvalues for successive factors are displayed in a simple line plot.

and the BB methods dating. Compared to the GDP model, the composite coincident model more accurately coincides with SARB's business cycle with a 15,2 per cent discrepancy between the two dating methods. However, in this case much of the discrepancy arises from the May 2002 to February 2003 period, where the model correctly predicts a slowdown in economic activity, although not officially dated by SARB. The discrepancy with SARB's reference turning points in dating the start of downward phases is also improved in this model, with the only significant difference occurring in the recession in the late 1980s. Overall, the composite coincident model outperforms the GDP model, more accurately dating the business cycle turning points. The BB method again dates many more cycles than either SARB-dated turning points or the composite coincident model dating.

[Figure 4 here]

5.3 Diffusion Model

The diffusion model applies PCA to 123 variables used in the determination of SARB's reference turning points of the business cycle. Not all the diffusion index data are used, due to inconsistency in starting dates and breaks in some of the variables. Figure 5 plots the first PC from this analysis. Similar to first PC of the composite coincident model, this PC also clearly shows the cyclicality in economic activity. However, it only explains about 15 per cent of the co-movement in the 123 variables.

[Figure 5 here]

Two diffusion models are fitted to the PCs, one including only the first PC, namely an MSMH(2)-AR(0) model; and the other including the first seven PCs, namely MSMH(2)-VAR(0). The presumption is that these models would more accurately represent aggregate business cyclicality, as compared to the composite coincident model and GDP, as more data are included from each sector. Two criteria are used for the selection of the seven PCs. First, only PCs that explain at least 4 per cent of the total variation in the dataset are used. This restricts the number to seven. Second, seven VAR models are estimated each time adding an extra PC. The model with the lowest BIC is chosen. The seven PCs explain close to 60 per cent of the overall variation in our 123 variables. The strong correlation structure present in the data allows for a close to seventeen-fold decline in the number of variables needed in the estimation step. Tables 4 and 5 present the results of the two diffusion models.

[Table 4 and 5 here]

Owing to the relatively small percentage of variation explained by the first PC, the MSMH(2)-AR(0) model poorly estimates the turning points of the business cycle and does not compare as favourably as other models with the business cycle dates published by SARB, with a 25,3 per cent discrepancy between the two dating methods. That said, the model still finds a significant difference in the means of each regime and accurately indicates the volatility differences between the two regimes. The transition probabilities show that over the sample period the average upward phase lasted just over 20 months (15 months based on the BB method), while the average downward phase lasted 45 months (24 months). However, due to the low explanatory power of the first PC (only 15 per cent), the model was not as effective in dating turning points as the seven PC diffusion and the composite coincident model.

The MSMH(2)-VAR(0) model performance is similar to the composite coincident model and therefore highly correlated with the movements of the SARB business cycle, with a discrepancy of only 15,8 per cent; again mainly as a result of the 2002–03 period. A clear pattern in the mean and variance of this model is present. Generally, regime 1 coefficients are negative and regime 2 coefficients are positive. Furthermore, similar to the MSMH(2)-AR(0) model, the variance during the downward phase (regime 1) is, on average, higher. The average duration of downward phases is estimated in this model at 31 months while the average upward phase is 30 months. Figure 6 plots the smoothed probabilities of both the diffusion models against SARB's business cycle.

[Figure 6 here]

6. CONCLUSION

In this paper we applied a Markov switching model and BB method to date the South African business cycle turning points and found that the model estimates generally coincide with the dating of SARB's business cycle turning points. Given the consensus that the business cycle refers to a cycle in aggregate economic activity, this paper moves away from only using GDP, to using PCA on the components of the composite coincident index and diffusion data, in order to model the aggregate co-movement in economic variables. This method was found to be more accurate at predicting business cycle turning points than GDP, the most common measure in studies of this nature. However, given the simplicity of the GDP approach, this cannot be effectively disputed. This paper also reveals that within the Markov switching framework, the mean and variance are sufficient estimators to determine accurate turning points in the South African economy, and no durational dependence or other dependent variables are necessarily required in the dating process. However, this could be investigated further.

This paper suffers from some caveats. First, the data are detrended using only one procedure, log differencing, therefore focusing on growth rate cycles rather than classical business cycles. This method was deliberately chosen to enable a comparison between the Markov switching output and SARB's business cycle reference turning points. Second, it is difficult to determine whether the advantages of statistical methods to detect the turning points of the business cycle outweigh the advantages of other algorithms such as the current method adopted by SARB. Third, the method applied above was unable to detect the current upswing in the business cycle, even though Krolzig (1997) states that one of the advantages of Markov switching models is their ability to detect recent regime shifts.[17] However, the SARB approach also requires a sufficient amount of lag before dating is possible.

Future work includes investigation into the impact of different detrending methods on the dating of business cycle turning points and testing for the inclusion of other dependent variables in the Markov switching model framework. Other types of non-linear models could also be estimated to provide further robust estimates of the turning points.

[17] This is due to the cut-off date of the data at the end of 2009. By extending the data to the most recent observation, we were able to date the turning point in mid-2009.

APPENDICES

Appendix A: Component of the composite coincident index

No.	Description	Transformation	Seasonally adjusted
1	Real gross value added: Non-agricultural sector at basic prices	Percentage change	✓
2	Employment: Total non-agricultural sector	Percentage change	✓
3	Retail and new vehicle sales	Percentage change	✓
4	Industrial production index	Percentage change	✓
5	Utilisation of production capacity in manufacturing	Differenced	✓

Appendix B1: Business cycle dating using the Markov switching procedure

		-		-		-		-	
Upward phase	**Duration**	**Upward phase**	**Duration**	**Upward phase**	**Duration**	**Upward phase**	**Duration**	**Upward phase**	**Duration**
		March 1982	–	February 1982	–			March 1982	–
April **1983 – June 1984**	15	November 1983 – November 1984	13	October 1983 – August 1984	11	October 1983 – June 1984	9	September 1983 – June 1984	10
April **1986** – February **1989**	35	March 1987 – August 1989	30	September 1987 – June 1989	22	July 1987 – April 1989	22	May 1987 – December 1989	32
June **1993** – November **1996**	42	August 1993 – September 1997	50	June 1993 – Nov 1996	42	February 1994 – December 1995	23	June 1993 – November 1996	42
September **1999** – November **2007**	99	June 1999 – October 2008	133	August 1999 – January 2002	30	December 1999 – November 2000	12	December 1999 – July 2001	20
				June 2003 – August 2007	51	December 2002 – July 2006	44	October 2002 – June 2007	57
Downward phase									
September **1981** – March **1983**	19	April 1982 – October 1983	19	March 1982 – September 1983	19	– September 1983	–	April 1982 – August 1983	17
July 1984 – March **1986**	21	December 1984 – February 1987	27	September 1984 – August 1987	36	July 1984 – June 1987	36	July 1984 – April 1987	34
March **1989 – May 1993**	51	September 1989 – July 1993	47	July 1989 – May 1993	47	May 1989 – January 1994	57	January 1990 – May. 1993	41
December **1996 –** August **1999**	33	October 1997 – May 1999	20	December 1996 – July 1997	32	January 1996 – November 1999	47	December 1996 – November 1999	36
				February 2002 – May 2003	16	December 2000 – November 2002	24	August 2001 – September 2002	14
December **2007** –	–	Nov 2008 –	–	Sep 2007 –	–	August 2006 –	–	July 2007 –	–

Appendix B2: Business cycle dating using the Bry–Boschan method

SARB's Dating		Bry-Boschan Method Gross Domestic Product		Bry-Boschan Method Composite Coincident		Du Plessis (2006) BBQ method Updated		Bry-Boschan Method Diffusion	
Upward phase	**Duration**	**Upward phase**	**Duration**	**Upward phase**	**Duration**	**Upward phase**	**Duration (q)**	**Upward phase**	**Duration**
April 1983 – June 1984	15	March 1983 – May 1984	15	March 1983 – June 1984	16	1983 Q3 – 1984 Q2	4	January 1983–October 1983	10
April 1986 – February 1989	35	June 1985 – August 1988	39	July 1985 – August 1988	38	1987 Q4 – 1989 Q1	6	June 1985 – April 1988	35
				November 1989 – October 1990	12			February 1991 – October 1992	21
		December 1992 – February 1995	27	September 1992 – September 1995	37	1993 Q1 – 1994 Q4	8	January 1994 – December 1994	12
June 1993 – November 1996	42	December 1995 – November 1996	12			1996 Q1 – 1996 Q4	4	December 1997 – August 1998	9
September 1999 – November 2007	99	December 1998 – May 2000	18	November 1998 – April 2001	30	1999 Q1 – 2001 Q1	9	July 1999 – March 2000	9
		December 2001 – August 2002	9	January 2003 – October 2004	22	2001 Q4 – 2003 Q1	6	March 2002 – February 2003	12
		December 2003 – November 2004	12	August 2005 – July 2006	12	2003 Q4 – 2008 Q2	19	February 2004 – April 2005	15
		December 2005 – February 2007	15						
Downward Phase									
September 1981 – March 1983	19							January 1982 – December 1982	12
July 1984 – March 1986	21	June 1984 – May 1985	12	July 1984 – June 1985	12	1984 Q3 – 1987 Q3	13	November 1983 – May 1985	19
March 1989 – May 1993	51	September 1988 – November 1992	51	September 1988 – October 1989	14	1989 Q2 – 1992 Q4	15	May 1988 – January 1991	33
				November 1990 – August 1992	22			November 1992 – December 1993	14
		March 1995 – November 1995	9	October 1995 – October 1998	37	1995 Q1 – 1995 Q4	4	January 1995 – November 1997	35
December 1996 – August 1999	33	December 1996 – November 1998	24			1997 Q1 – 1998 Q4	8	September 1998 – June 1999	10
		June 2000 – November 2001	18	May 2001 – December 2002	20	2001 Q2 – 2001 Q3	2	April 2000 – February 2002	23
		September 2002 – November 2003	15			2003 Q2 – 2003 Q3	2	March 2003 – January 2004	11
		December 2004 – November 2005	12	November 2004 – July 2005	9	2008 Q3 –	–	May 2005 – December 2009	56
December 2007 –	–	March 2007 –	–	Aug 2006 –	–				

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Tables and figures

Table 1: Bry and Boschan determination of turning points

1. Determination of extremes and substitution of values.
2. Determination of cycles in a 12-month moving average (extremes replaced).
   a. Identification of points higher (or lower) than 5 months on either side.
   b. Enforcement of alternation of turns by selecting highest of multiple peaks (or lowest of multiple troughs)
3. Determination of corresponding turns in Spencer curve (extremes replaced).
   a. Identification of highest (or lowest) value within +/- 5 months of selected turn in 12-month moving average.
   b. Enforcement of minimum cycle duration of 15 months by eliminating lower peaks and higher troughs of shorter cycles.
4. Determination of corresponding turns in short-term moving average of 3 to 6 months, depending on months of cycle dominance.
   a. Identification of highest (or lowest) value within +/- 5 months of selected turn in Spencer curve.
5. Determination of turning points in unsmoothed series.
   a. Identification of highest (or lowest) value within +/- 4 months, or months of cycle dominance term, whichever is larger, of selected term in short-term moving average.
   b. Elimination of turns within 6 months of beginning and end of series.
   c. Elimination of peaks (or troughs) at both ends of series that are lower (or higher) than values closer to the end.
   d. Elimination of cycles whose duration is less than 15 months.
   e. Elimination of phases whose duration is less than 5 months.
6. Statement of final turning point.

*Table 2: MSMH(2)-AR(0) model of gross domestic product**

Coefficients	**GDP MSMH(2)-AR(0)**
μ_1	-0.007043 (0.001804)
μ_2	0.038352 (0.001014)
σ_1	0.000226 (0.000035)
σ_2	0.000140 (0.000016)
P_{11}	0.965041 (0.016081)
P_{22}	0.977817 (0.010004)
Diagnostics	Log-likelihood = 953.34766404 BIC = -8.767 JB-stat = 2.53

* Standard errors are included in brackets.

*Table 3: Composite coincident MSMH(2)-AR(0) model**

Coefficient	**CC *MS*MH(2)-AR(0)**
μ_1	-0.057828 (0.004700)
μ_2	0.066157 (0.003671)
σ_1	0.003152 (0.000343)
σ_2	0.001526 (0.000190)
P_{11}	0.970301 (0.012984)
P_{22}	0.964383 (0.014729)
Diagnostics	Log-likelihood = 514.66982284 BIC = -6.143 JB-stat = 99.644

* Standard errors are included in brackets.

*Table 4: Diffusion MSMH(2)-AR(0) model**

Coefficient	MSMH(2)-AR(0)
μ_1	-0.352580 (0.049104)
μ_2	0.716906 (0.074100)
σ_1	0.216265 (0.022137)
σ_2	0.103992 (0.025836)
P_{11}	0.977925 (0.010120)
P_{22}	0.951184 (0.021075)
Diagnostics	Log-likelihood = -209.92889153 BIC = -1.841 JB-stat = 150.340

* Standard errors are included in brackets.

*Table 5: Thirteen-principal component diffusion MSMH(2)-VAR(0) model**

Coefficient	Regime 1	Regime 2
μ^1	-0.489174 (0.043135)	0.506595 (0.041676)
μ^2	0.032712 (0.052773)	-0.033864 (0.045910)
μ^3	-0.102724 (0.038020)	0.106388 (0.046434)
μ^4	-0.017621 (0.042416)	0.018250 (0.039602)
μ^5	0.066361 (0.037110)	-0.068728 (0.030453)
μ^6	-0.035527 (0.040091)	0.036795 (0.031054)
μ^7	-0.013572 (0.024217)	0.014054 (0.032235)
σ^1	0.201096 (0.022623)	0.193167 (0.024949)
σ^2	0.166714 (0.019551)	0.227374 (0.026207)
σ^3	0.416958 (0.046514)	0.139884 (0.015984
σ^4	0.236272 (0.028998)	0.207414 (0.022856)
σ^5	0.205569 (0.023324)	0.122608 (0.014274)
σ^6	0.324895 (0.038037)	0.098413 (0.011344)
σ^7	0.268843 (0.031586)	0.159464 (0.018224)
P	0.967735 (0.013624)	0.966130 (0.014018)
Diagnostics	Log-Likelihood = -1467.82757740 BIC = -11.381 JB-stat = 49.072	

* Standard errors are included in brackets.

Figure 1: Density plot of gross domestic product

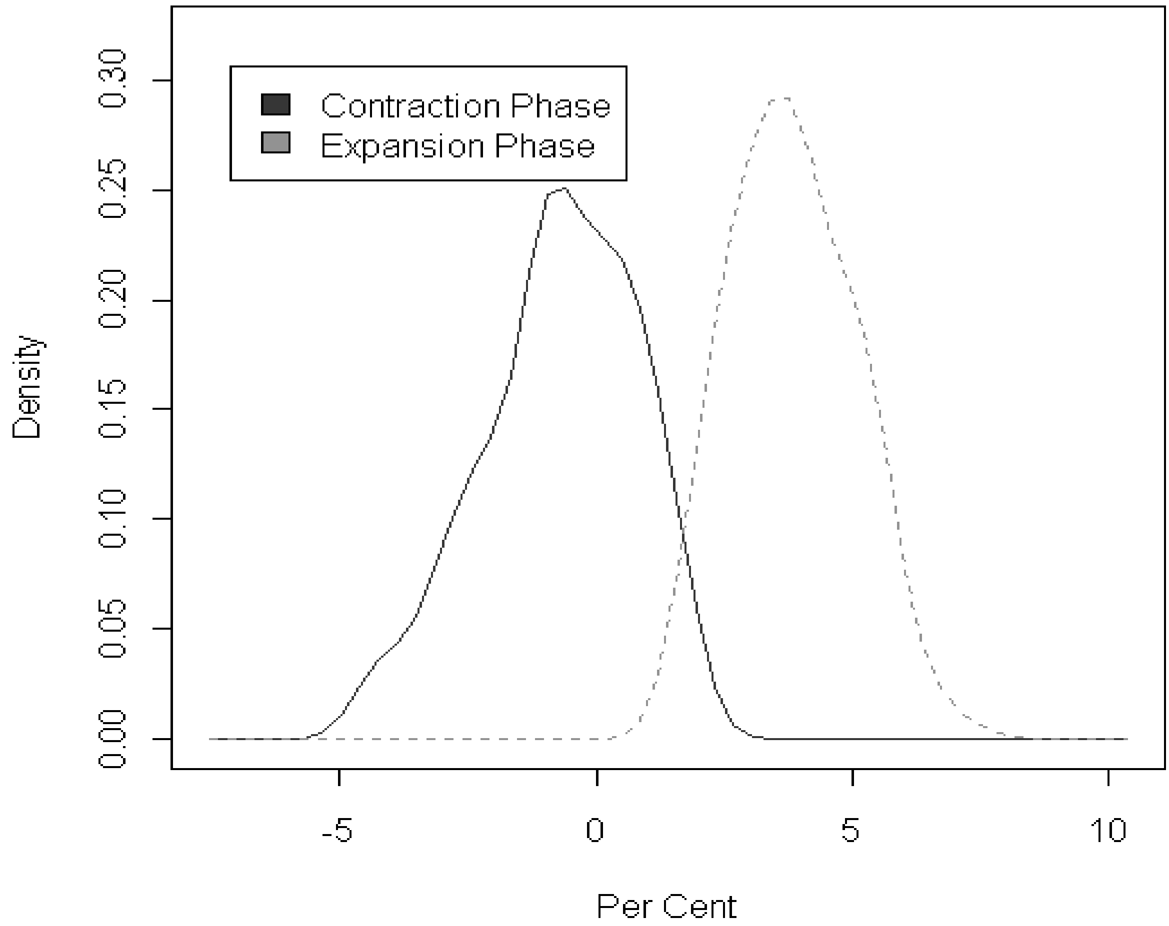

Figure 2: Gross domestic product MSMH(2)-AR(0)

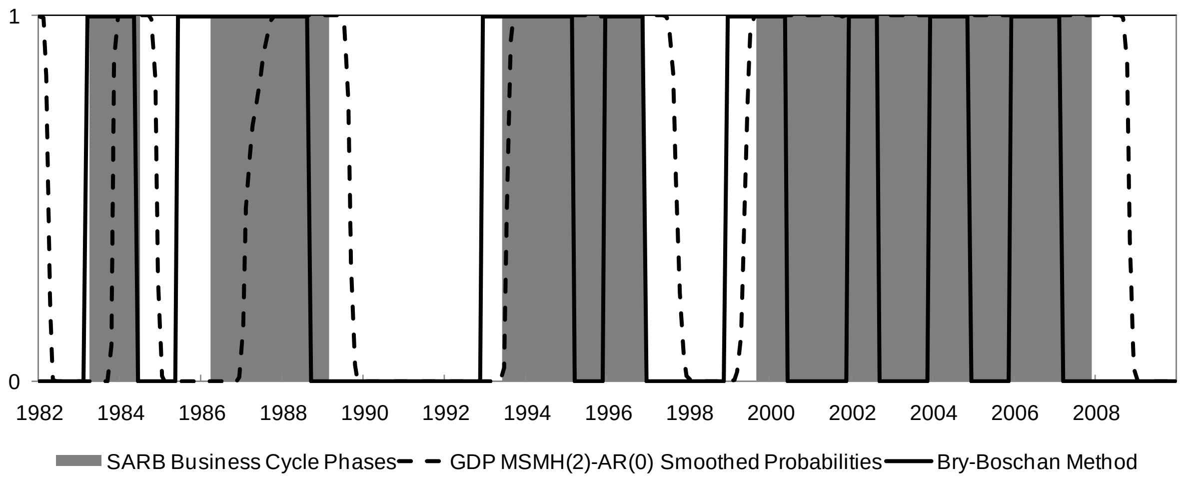

Figure 3: Composite coincident first principal component

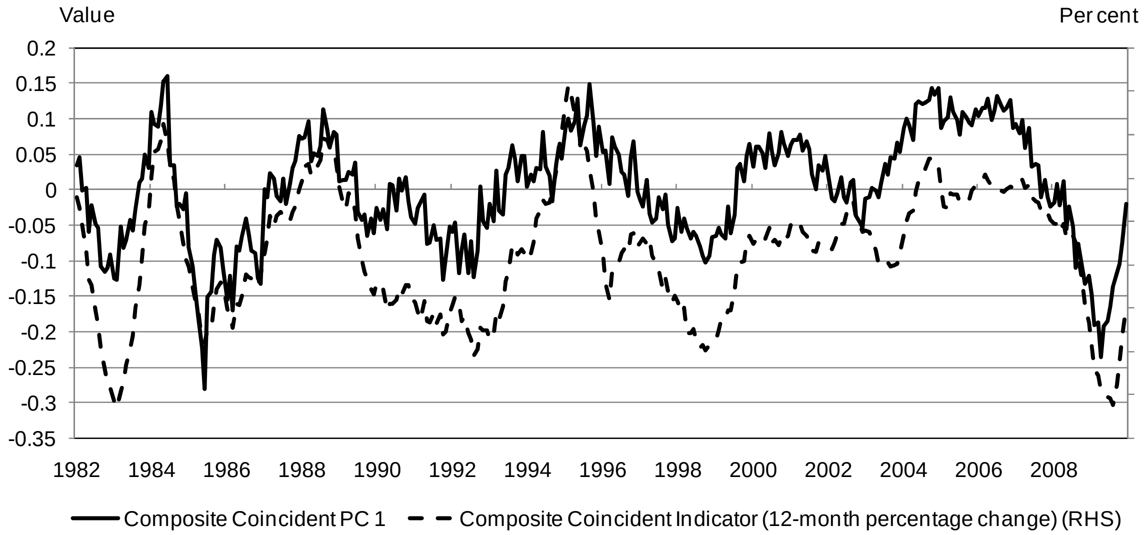

Figure 4: Composite coincident MSMH(2)-AR(0)

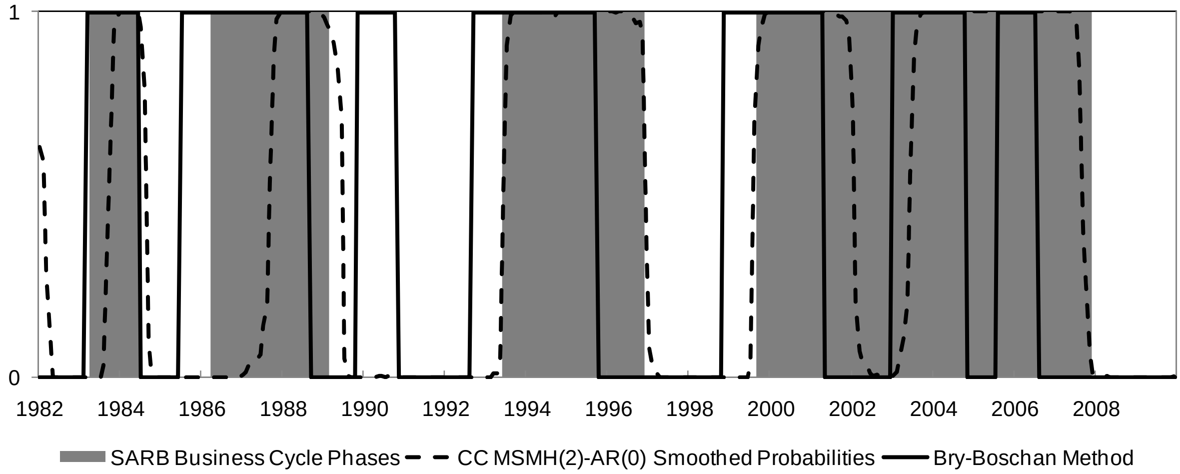

Figure 5: Diffusion first principal component

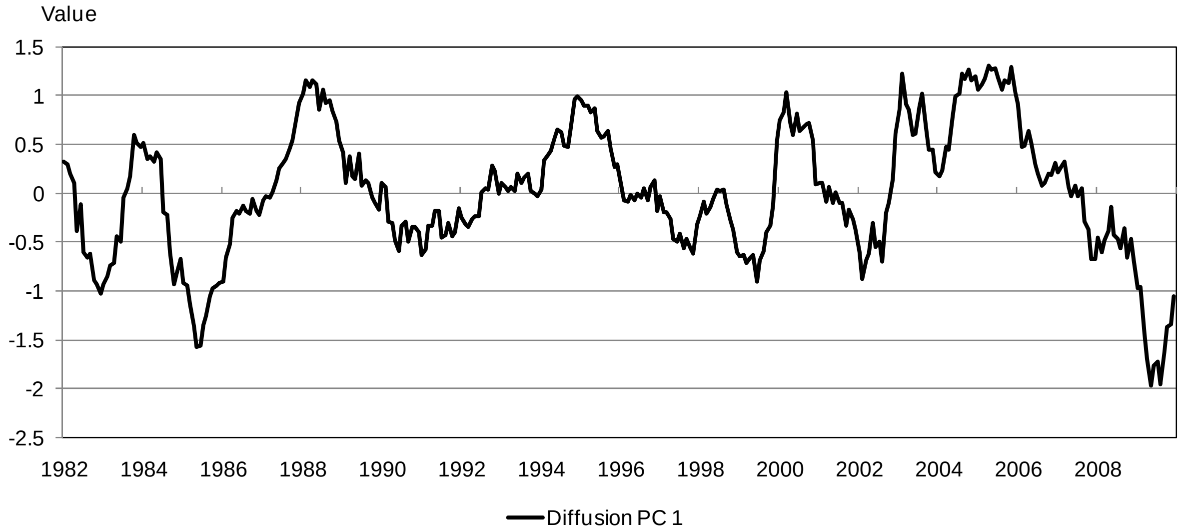

Figure 6: Diffusion MSMH(2)-AR(0) and diffusion MSMH(2)-VAR(0)