



**Band-pass filters and business cycle analysis: High-frequency and medium-term deviation cycles in South Africa and what they measure**

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# BAND-PASS FILTERS AND BUSINESS CYCLE ANALYSIS: HIGH-FREQUENCY AND MEDIUM-TERM DEVIATION CYCLES IN SOUTH AFRICA AND WHAT THEY MEASURE

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## Abstract

Many analysts use band-pass filters to remove so-called permanent components from output and then study the remainder, which is then termed the “business cycle”. Building on the critique of these deviation cycles by Harding and Pagan and on the recent work on the medium-term persistence of business cycles by Comin and Gertler, we study the extent of information loss accompanying this practice. Specifically, we compare the properties of deviation cycles obtained when allowing and disallowing medium-run information to be included with the permanent component and show the dramatic differences in stylized facts. The paper then considers the economic context of high-frequency and medium-term deviation cycles. The results suggest that the high-frequency deviation cycle is not an appropriate measure of demand shocks, which are equally approximated by the medium-term deviation cycle – even though the two cycles differ significantly in terms of persistence, volatility and co-movement with cycles in the US, UK, Europe and Australia. The medium-term deviation cycle appears to capture the cumulated demand and supply shocks to the economy, which is relevant for medium-run analysis but is not useful for business cycle research. The study focuses on four sample periods, one longer and one shorter sample period as well as one including and one excluding the recent financial crisis period, and the results therefore also shed light on whether and how the financial crisis and structural change in South Africa may alter conclusions.

## 1 INTRODUCTION

Output fluctuations in the short-run have longer-run implications for output growth, as they carry over into longer-run fluctuations (Comin and Gertler 2006). The deep recession following the recent financial crisis is likely to lead to further interest in the properties of and relationships between output fluctuations at different time horizons. Frequency filters are popular tools in the study of fluctuations at a specific time horizon. However, Harding and Pagan (2002; Harding and Pagan 2002; Harding and Pagan 2005) underline the problematic nature and non-uniqueness of these “deviation cycles”, which are obtained by removing so-called permanent components from output data. These and other authors (Canova 1998; Zarnowitz and Ozyildirim 2006) also highlight the significant loss of information which accompanies all time series filters, a particular problem for studies aimed at business cycle description or stylized facts.

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The paper studies fluctuations at different time horizons in South African output. The South African economy is an appropriate case, given that output has experienced significant short- and medium-term fluctuations over the past four decades (Du Plessis, Smit *et al.* 2008). The paper has two specific goals. Firstly, the paper reconsiders the properties of the South African business cycle, as measured by the frequency-filtered deviation cycle. Specifically, the paper studies the information loss resulting from the use of deviation cycles of a particular frequency range by comparing the persistence of short-term and medium-term deviation cycles in South Africa and by re-assessing their co-movement with similar cycles in the US, UK, Europe and Australia. Secondly, the paper studies the economic content of the short-term and medium-term deviation cycle by studying how well these two deviation cycles capture demand and supply shocks identified in earlier research.

The following section presents a brief literature review of the Harding and Pagan business cycle taxonomy and the position of the current research on the so-called “medium-term business cycle”. This is followed by the data description and methodology, after which the results on properties and co-movement are reported and discussed. The conclusion summarizes the findings.

## 2 LITERATURE REVIEW

Business cycle research depends on a clear definition of “cycle”. Harding and Pagan (2005) develop a taxonomy of business cycle concepts, distinguishing between classical, deviation and growth rate cycles. The classical cycle, the original concept used by Burns and Mitchell (1946) and most central banks, refers to the cycle in the levels of the output series. Deviation cycle analysis involves identifying and removing a so-called “permanent component” from the output series – the remainder is then a set of serially correlated deviations and is called a deviation cycle (or frequently also a growth cycle) (see Canova (1998) for a critical summary). Finally, a growth rate cycle refers to a cycle in growth rates, capturing periods of accelerating and decelerating growth, and is a special type of deviation cycle, with the previous value of output taken as the permanent component. Mainstream business cycle research focuses predominantly on deviation cycles, but Harding and Pagan (2002) show that the permanent component *cannot* be identified uniquely, regardless of the filter used (whether it is the Hodrick-Prescott (1997) filter or one of the various band-pass filters (Baxter and King 1999; Christiano and Fitzgerald 2003)). Harding and Pagan also show that removing permanent components is not the same as removing permanent *shocks*. Even if it were possible, business cycle research would suffer from the removal of permanent shocks, given the insights from the real business cycle literature.

The Harding and Pagan critique of deviation cycles suggests that the practice of shifting all information beyond the short term into a permanent component may be associated with significant loss of information relevant for business cycle research. Business cycles are not transitory disturbances to a smooth long-run growth path (Solow 2000). Business cycles have medium-term effects and recent work compares the properties of medium-term and short-term deviation cycles. For example, an important paper by Comin and Gertler (2006) compare the deviation cycle in the US where the permanent component contains all information beyond eight years, with the deviation cycle where the permanent component contains all information beyond 50 years. They label the former the “business cycle” and the latter the “medium-term cycle” and show that business cycles generate medium-term cycles via endogenous technology dynamics. Comin, Loayza, Pasha and Servén (2009) use the same concepts to show that country differences in technology dynamics ensure that short-term fluctuations in one developed country (the US) are propagated into medium-run fluctuations in a developing country (Mexico).

While medium-term cycle research seems to promise better understanding of business cycle dynamics and propagation, this research is still exposed to the Harding and Pagan critique, given that it is predominantly based on frequency-filtered data. Nevertheless, the medium-term research sheds light on the information loss accompanying business cycle analysis by showing how properties

are altered when considering different frequency ranges. This paper evaluates the plausibility of frequency-based deviation cycles as measures of the business cycle, both from a short-term and a medium-term perspective. The paper therefore first compares short-term and medium-term deviation cycles. If the short-term and medium-term deviation cycles produce different conclusions on business cycle properties, the paper then asks what business cycle information each cycle is capturing. The problem with the frequency-based deviation cycle is that it is a purely statistical tool that has no inherent economic foundation. It is therefore necessary to compare the frequency-based deviation cycle with the predicted deviation cycle from an economic model in order to assess the extent to which a frequency-based deviation cycle is a plausible measure of the business cycle. For example, the short-term deviation cycle in one country may approximate demand shocks, but may not adequately capture business cycles if supply shocks also play a role in short-term economic fluctuations. A study of the plausibility of the frequency-based deviation cycle therefore requires choosing country-specific studies – and this paper focuses on South Africa.

The paper studies the properties of short-term and medium-term deviation cycles for South African output and compares the properties of South African deviation cycles with those of similar deviation cycles in US, UK, European and Australian output. Harding and Pagan show that the choice of business cycle concept has implications not only for stylized facts concerning cyclical properties but also for stylized facts concerning co-movement. This argument is important, given that business cycle synchronization in South Africa has received extensive attention following the reintegration of the South African economy into international trade and finance networks since 1994, as well as the effects of increasing globalization on output volatility. Recent work by Kabundi (2009), employing structural dynamic factor analysis, studies the relationship between South African and US output over the period 1985 to 2003. The analysis confirms output co-movement between the two countries and explores various transmission mechanisms. Kabundi and Loots (2007) perform a similar study, finding strong co-movement between South Africa and most member countries of the South African Development Community. Botha (2010) further studies interactions among South African and other developing country business cycles using similar techniques, uncovering increased output synchronisation during common shock periods. However, Du Plessis (2006) employs a non-parametric turning point approach to investigate the properties of business cycles in South Africa and other emerging markets as well as co-movement and finds little evidence of co-movement. Boshoff (2005) follows the same turning point approach and finds little co-movement between various concepts of the South African business cycle and similar cycles in local and international financial variables. The Du Plessis and Boshoff findings are based on a classical cycle concept, whereas much of the other research focuses on deviation cycles. Again, it is necessary to consider to what extent the information loss from removing permanent components influences co-movement results. This paper therefore considers the implications of using different frequency-based deviation cycles for co-movement analysis, in order to consider whether the medium-term deviation cycle offers evidence contrary to that based on conventional short-term deviation cycles.

### 3 DATA

The paper focuses on real output, measured by quarterly real gross domestic product (GDP). Although some studies rely on industrial production, this data is increasingly less representative of overall output movements, given the rise of the services economy. One section of the paper studies co-movement properties and we choose the USA, UK, Europe and Australia. The US is chosen for its importance in the global business cycle, Europe and the UK for their importance as trading and finance partners to South Africa, and Australia for its similarity to South Africa as a traditionally commodity-based economy.

Output data are obtained from both the IMF's International Financial Statistics (IFS) database and the particular country's national data collection agency. Table 1 reports the sources and sample

periods of the country output data. A comparison of the two data series for each country shows strong similarity and we use the IFS data as basis. All series are seasonally adjusted.

As shown in Table 1, we choose a sample period commencing in the first quarter of 1960 and terminating in the first quarter of 2010. However, Du Plessis, Smit and Sturzenegger (2008) raise concerns about the changes in monetary policy regime over this period, arguing that one should also consider a shorter sample period commencing in the 1980s, given the significant monetary policy changes introduced during the eighties. Also, as noted earlier, a shorter sample period allows the paper to consider whether co-movement results are robust. We therefore also use a short sample period commencing in the first quarter of 1980 and terminating in first quarter 2010.

As argued earlier, and as illustrated in Figure 1, the recent synchronized output contraction across the different countries suggests that the decision to include data from the financial crisis period may have implications for co-movement results. The paper therefore considers two sample periods: one that includes and one that excludes data from 2007 onwards.

The box-and-whisker plots of Figure 3 and Figure 4 shed further light on the importance of sample period for business cycle research. The box-plots describe the sample distribution of output growth for the different countries for each of the four sample periods (i.e. the longer and shorter sample periods, each with and without data from the recent crisis period). Mean output growth is highest for South Africa and Australia over the longer sample period, although output growth is generally more volatile in these countries than growth elsewhere, barring some outliers. The longer sample period, however, masks the relatively poor performance of the South African economy in the eighties and early nineties: the right hand graph for the shorter sample period shows that the lowest 25% of data points were mostly negative. Furthermore, the Australian economy appears much more stable in the shorter sample periods, while the South African economy remains relatively more volatile.

Figure 3 and Figure 4 are virtually identical but for the significantly higher number of outliers in Figure 3: the box-plots in Figure 3 classify a number of the data points from 2007 onwards as outliers, especially for the UK and Europe. This suggests that it is important to account for different sample periods when studying the properties of South African output fluctuations and their relation to similar fluctuations elsewhere.

The following section describes the empirical methodology for, firstly, investigating the properties and co-movement of different frequency-based deviation cycles and, secondly, assessing the plausibility of a frequency-based deviation cycle as a measure of the business cycle.

## 4 METHODOLOGY

### 4.1 Extracting deviation cycles

As mentioned earlier, a clear definition of the business cycle is crucial to an analysis of business cycle properties. This paper employs the deviation cycle concept. A deviation cycle concept assumes that output can be decomposed uniquely into a permanent (or “trend”) and a cyclical component, barring seasonal and irregular noise. At time  $t=1, \dots, N$ , let  $D_t$  be the deviation cycle,  $Y_t$  observed real output and  $T_t$  trend output, such that:

$$D_t = Y_t - T_t \tag{1}$$

The permanent component and deviation cycle is unobserved and must therefore be estimated:

$$\check{D}_t = Y_t - \check{T}_t \tag{2}$$

As mentioned, there is a range of approaches to calculating an estimate  $\check{D}_t$ . Estrella (2007) distinguishes between a frequency-filtering approach, concerned with extracting a specific frequency range, and signal filtering, concerned with extracting a stationary component which contains information across all frequencies. Given the previous discussion on the impact of specific time horizons

for business cycle research, notably the medium run, this paper follows a frequency-extraction approach. Specifically, frequency ranges are extracted using a band-pass filter. The literature suggests two finite sample approximations for the ideal band-pass filter: the Baxter and King (1999) (BK) filter and the Christiano and Fitzgerald (2003) (CF) filter. The BK filter imposes a specific lag length and symmetry (assigning equal-weight leads and lags of the same magnitude), while the CF filter allows the data to dictate weights. The two filters produce similar results at high frequencies, but research suggests that the CF filter outperforms the BK filter where the focus is on identifying longer-term fluctuations (Zarnowitz and Ozyildirim 2006). Given the paper’s focus on both the short and medium run, the CF filter is used to extract frequency ranges and the deviation cycles are denoted  $\check{D}_t^f$ .

This paper focuses on both a short-term and a medium-term deviation cycle, which requires an explicit definition of the frequency ranges associated with “short-term” and “medium-term”. The short-term, or high-frequency, deviation cycle is that component of output corresponding to a frequency range of 6 to 32 quarters. The medium-term deviation cycle is defined as the sum of the high-frequency and the medium-frequency components. The medium-frequency component is that component of output related to a frequency range of 32 to 200 quarters, which corresponds to the range used by Comin and Gertler (2006) in their US study. Therefore, the medium-term cycle covers the frequency range 6 to 200 quarters.

## 4.2 Measuring the properties of extracted deviation cycles

The study focuses on the variance and covariance properties of business cycles. As far as variance properties are concerned, the paper compares the extent of volatility of the different deviation cycles as well as the relationship between business cycle and overall variance, known as persistence.

Formally, the paper measures volatility of a deviation cycle using standard deviation with a 95% confidence interval. Following Giannone and Reichlin (2005) the paper measures persistence by comparing the standard deviation of the growth rate with the standard deviation of an extracted component related to the long run. The paper considers two such permanent components, one including all information beyond business cycle durations (i.e. including medium-frequency information defined earlier, as well as low-frequency information) and one including only information beyond the medium run (i.e. only low-frequency information). The former corresponds more closely with the HP trend used to measure persistence in Giannone and Reichlin (2005).

Apart from the variance properties of a particular business cycle, the covariance properties among business cycles are also an important feature frequently investigated. A range of empirical tools measure business cycle co-movement, including tests for common features (Engle and Kozicki 1993; Vahid and Engle 1993) and tests for cointegration (Engle and Granger 1987). The concept of co-movement as rank reduction underlies these time series measures – a concept that may be related but not identical to the intuitive interpretation of co-movement as correlation. A concept intuitively closer to co-movement is dynamic correlation, which can be interpreted as correlation applied to a specific frequency component (Croux, Forni *et al.* 2001). Dynamic correlation between two series is the correlation between the same frequency ranges of the spectral densities of two series. This concept is relevant for our question, which is to investigate the frequency-dependence of co-movement at medium-term time horizons.

As argued later, to account for structural change in the economy, the full-sample calculations are followed by correlations calculated on a rolling basis using a sample period length of 15 years. Estimates are reported with 95% confidence intervals.

## 4.3 Assessing the economic content of the extracted deviation cycle

If variance and covariance properties differ among various deviation cycles, it is necessary to ask what a particular frequency-based deviation cycle is actually measuring. The time series filtering literature

aims to derive an unbiased efficient estimator of  $D_t$ , but does not deal with the identification problem in deviation cycle analysis. Filters are statistical instruments without inherent economic meaning: one cannot know whether a candidate filter will produce an optimal estimator of the unobserved deviation cycle. The identification problem is the main thrust of Harding and Pagan’s critique of deviation cycles, discussed earlier. An alternative approach uses economic information to identify  $T_t$  and, hence,  $D_t$ . Du Plessis, Smit and Sturzenegger (2008) represent a recent attempt at estimating the South African business cycle using econometric techniques. Specifically, these authors identify aggregate demand and supply shocks using a structural VAR (SVAR) of the South African economy and then cumulate the demand shocks (of fiscal and monetary origin) to generate a demand-based measure of the business cycle. An economics-based estimator, such as the SVAR estimator,  $\check{D}_t^{SVAR}$ , provides a benchmark with specific economic meaning against which the performance of a non-economics filter-based estimator,  $\check{D}_t^f$ , can be assessed. Such a benchmark is appropriate given that filters do not produce unique trend estimates: it tells the analyst what a particular filter-based deviation cycle measures. The paper compares  $\check{D}_t^{SVAR}$  and  $\check{D}_t^f$  by assessing variance and covariance properties in the same way as described previously.

## 5 EMPIRICAL RESULTS

### 5.1 Band-pass frequency filtering

Figure 4 shows that output in South Africa steadily expanded throughout the sixties and early seventies, stagnated especially in the 1980s and early 1990s, and then, since 1999, expanded unabated until the recent financial crisis:

Figure 5 presents the results obtained when applying the CF filter to South African output data. The figure shows both the medium-frequency component as well as the “medium-term deviation cycle”. The medium-term deviation cycle is the sum of the medium-frequency and high-frequency components. Therefore, the difference between the two lines in Figure 5 is the high-frequency deviation cycle. All values are expressed as a percentage of the permanent component, i.e. of the lower-frequency component.

Visual inspection of Figure 5 reveals the following:

- (i) The medium-term deviation cycle starts its decline relative to the permanent component in the early seventies. The cycle falls below the permanent or low-frequency component from the late eighties, as the impact of anti-Apartheid sanctions and the subsequent debt standstill depressed economic growth.
- (ii) The cycle started recovering after the democratic transition in 1994. Note that the medium-term cycle has only recently, since 2005, moved above the permanent component. This appears consistent with the recent output gap estimation by Du Plessis *et al.* (2008), who found growth only recently caught up with long-run trend growth. However, it is incorrect to equate the two, given that one cannot interpret the permanent component as an output gap estimate.
- (iii) Furthermore, since about 2002, the short-term deviation cycle is smaller in comparison with the medium frequency component. This implies that strong output growth since 2003 could be ascribed to a longer-term momentum, rather than short-term spikes, and is consistent with the findings of Laubscher (2004).

The visual inspection suggests that the extracted component exhibits some features, including direction of movement, consistent with those identified in previous empirical research. However, such commonality does not indicate whether the medium-term deviation cycle estimate is a plausible representation of the *true deviation cycle*. Nor does such commonality indicate that the medium-term deviation cycle is a plausible representation of the classical business cycle. The plausibility

of the deviation cycle is best measured by comparing the extracted cycle with the cycle identified from economic information, for example via an econometric model. This is attempted in the first empirical part.

It is useful to evaluate the impact of sample period on the extracted component. Figure 6 compares the medium-term cycle suggested by data including and data excluding the recent financial crisis period.

The graph suggests little difference until 2000, but the average estimate for the 2000-2006 period is altered by roughly 1%, as calculated in the first two columns of Table 2. Similar estimates for the shorter sample period (commencing in 1980) suggest that the inclusion of the financial crisis period data does not significantly alter results for the 2000-2006 period – see last two columns of Table 2.

Medium-term deviation cycles for US, UK, European and Australian output are obtained in similar fashion. The graphical results are reported in Appendix A. Unit root tests indicate the presence of unit roots in medium-term deviation cycles for all countries, regardless of sample period and lag order. The subsequent correlation and standard deviation calculations account for the presence of these unit roots.

As noted earlier, the frequency-based deviation cycle may entail significant information loss and this information loss can be studied by considering how the choice of frequency range affects one's conclusions on the volatility and persistence of the South African business cycle and its co-movement with cycles in its major trading partners. Results suggest that choice of frequency range is important, which then leads to the question of what a particular frequency-based deviation cycle is measuring. To this end, the paper compares the frequency-based deviation cycle, which is a *statistical* measure of the business cycle, with an *economic* measure of the South African deviation cycle, provided by demand and supply shocks from a structural VAR, as reported by Du Plessis *et al.* (2008).

## 5.2 Volatility and persistence properties of frequency-based deviation cycles

A useful first comparison of the high-frequency cycle and the medium-term cycle involves a comparison of volatility, as measured by the sample variance. If confidence intervals for the sample variance do not overlap for the two series, one may conclude that the high-frequency cycle captures business cycle information distinct from the information captured by the medium-term cycle ... (Comin and Gertler 2006). Cycles with overlapping confidence intervals may yet be capturing distinct information: non-overlapping is a sufficient though not a necessary condition for concluding that cycles are distinct. However, overlap requires further investigation and a comparison of confidence intervals is therefore a useful first step.

Figure 7 compares the medium-term deviation cycle and high-frequency deviation cycle in South African output. The medium-term cycle is more volatile compared to the high-frequency cycle: the amplitude of the medium-term cycle is 8% of output compared to the amplitude of 2% for the high-frequency cycle.

Table 3 compares the standard deviation (with 95% confidence interval) for the high-frequency deviation cycle, the medium-frequency component, and the medium-term deviation cycle.

The medium-term deviation cycle is more volatile than the high-frequency deviation cycle. A finding of higher medium-term volatility is similar to that of Comin and Gertler ... (2006) for the US, although the results above suggest a sharper difference in relative volatility of the two cycles in South Africa: where the medium-term deviation cycle in the US is roughly twice as volatile as the high-frequency deviation cycle, it is closer to four times for South Africa. The results for the shorter and longer sample periods are similar, although the volatility of the medium-frequency component in the shorter period is lower. Results based on sample periods including the financial crisis period are not significantly different from results for sample periods excluding the crisis period. More important for our comparison, the results confirm that the confidence intervals for the medium-frequency and high-frequency components do not include zero and do not overlap, which indicate that



the two components capture statistically distinct information. If the high-frequency and medium-term deviation cycles are distinct concepts and have different volatility properties, it is insightful to compare other properties, such as persistence.

Business cycle persistence is measured by the ratio of output growth to underlying “trend” growth (or, as Harding and Pagan defined it, growth in the permanent component). By definition, the trend associated with the high-frequency deviation cycle is measured by output from which the high-frequency component has been removed. Similarly, for the medium-term deviation cycle, the trend is measured by output minus both high- and medium-frequency variation. Table 4 reports the ratios between output growth and these trends for each of the four different sample periods:

High-frequency deviation cycles persist: high-frequency fluctuations affect the remainder of output fluctuations at lower frequencies, regardless of choice of sample period or inclusion of the financial crisis period. In contrast, medium-term deviation cycles do not persist, a result that is even stronger for the shorter sample period starting in the 1980s. Therefore, one’s view of business cycle persistence depends crucially on one’s view of whether the high-frequency or the medium-term deviation cycle is the better business cycle measure.

A comparison of the high-frequency cycle and the medium-term deviation cycle is not limited to a comparison of volatility and persistence properties. Frequency filters are commonly employed to study co-movement among international business cycles. It is therefore important to consider the impact of choice of frequency range. It is also important as differences in the volatility and persistence properties of deviation cycles do not necessarily imply differences in co-movement results for these deviation cycles. The high-frequency and medium-term deviation cycles may yet exhibit the same level of co-movement with similar cycles in other countries. The following section considers co-movement properties.

### 5.3 Co-movement properties of frequency-based deviation cycles in South Africa and its major trade partners

Figure 8 reports high-frequency and Figure 9 medium-term deviation cycles for South Africa and a selection of its developed country trade partners (the US, UK, Europe and Australia) for the longer sample period. Both graphs suggest significant co-movement among the cycles of the developed countries and broadly similar movements for the high-frequency cycle in South Africa, but much less similarity between South African medium-term cycles and those of developed countries.

Co-movement for both the high-frequency deviation cycle and the medium-term deviation cycle can be investigated using dynamic correlation. Table 5 reports the dynamic correlation estimates for the high-frequency deviation cycle and include both contemporaneous and lagging correlations (South Africa lagging for both two and four quarters).

The correlation between high-frequency deviation cycles in South Africa and Australia is statistically significant (different from zero), regardless of sample period, at lags of zero to two quarters. The size of the correlation is generally around 0.4. The results also suggest correlation with similar deviation cycles in the UK, US and Europe in the shorter sample period containing more recent data points than in the longer sample period. These correlations are lower, usually around 0.3.

Table 6 repeats the calculations for the medium-term deviation cycle. Correlations are calculated on data in first differences, given non-stationarity. The majority of conclusions based on levels data are similar, although correlations are mostly higher than those obtained for data in first differences.

The conclusions can be summarized as follows. Firstly, South African and Australian medium-term deviation cycles have statistically significant correlation at zero to two-quarter lags, regardless of length of sample period and regardless of the inclusion of the financial crisis period. The level of correlation remains around 0.4. Secondly, South African and European medium-term deviation cycles also share a correlation of around 0.2 at zero to two-quarter lags regardless of length of sample period. However, the inclusion of the financial crisis period has a significant impact: correlation is significantly higher once the crisis period is included – which suggests that increased synchronization

during the recent crisis affects the average estimate. Thirdly, for the US and UK we find correlation at two quarter lags of around 0.3-0.4 and this is generally higher for the shorter sample period. Conclusions are again sensitive to the inclusion of the financial crisis period.

At first glance, the results indicate that co-movement findings are less affected by choice of frequency range. However, the correlation estimates presented above are average figures calculated over a fixed sample period, which includes both the volatile period of political isolation in the 1980s as well as the subsequent period of liberalization. The South African economy has also experienced significant structural change since the 1980s – moving increasingly towards a services-based economy. It may be more informative to calculate rolling correlations over sub-periods of the larger sample period to study the evolution of these correlations (Peiró 2002). Figure 10 and 11 report these rolling correlations for sub-periods of 15 years, with 95% confidence intervals, beginning in 1980Q1. Similar calculations can be performed for the longer sample period starting in 1960Q1.

The horizontal axis shows the end date for each rolling period: the first is 1994Q4, which is 15 years after the starting point of 1980Q1. The conclusions from Figure 10 can be summarized as follows. First, there is no statistically significant correlation between the SA high-frequency deviation cycle and that of either Australia or the US for most of the rolling sample periods (the confidence intervals usually include zero). Second, co-movement with Europe has become more important in recent years, but much of this occurred during the financial crisis period. Third, there is a statistically significant correlation between SA and UK high-frequency deviation cycles of around 0.4. Although the correlation has gradually declined over the 1990s, it has also increased during the period including the financial crisis.

Figure 11 presents the rolling correlation results for the medium-term deviation cycle. The conclusions are similar to those obtained for the high-frequency deviation cycles in Figure 10. While co-movement with Australia is initially important, it is not statistically significantly different from zero for most of the rolling sample periods – although correlation increases during the financial crisis period. Co-movement with the US has been slowly declining towards zero over much of the period, although the correlation again increases during the crisis period. For the UK, co-movement rises to approximately 0.6 in 2000, but strongly declines thereafter. For Europe, co-movement is consistently around 0.4.

The results for rolling correlations and fixed correlation are clearly different – with less support for co-movement from the rolling correlations. More important for this paper, results for the medium-term and high-frequency deviation cycles differ when focusing on rolling correlations. The direction of movement may be broadly similar, but medium-term deviation cycle co-movement seems to be more variable than high-frequency co-movement. This is likely the result of South Africa's strong medium-term improvement relative to long-run trend during the 2000s (refer back to Figure 9). Apart from this, there are also other differences: for example, the decline in co-movement with the US occurs much earlier for the high-frequency deviation cycle, while the size of correlation also differs depending on frequency range.

In general, choice of frequency range matters for business cycle findings. If the high-frequency and medium-term deviation cycles are distinct concepts and produce different conclusions on business cycle properties related to volatility, persistence and co-movement, what business cycle information is each cycle capturing? The problem with the frequency-based deviation cycle is that it is a statistical tool that does not have an inherent economic foundation. It is therefore necessary to compare the statistical results with the predicted deviation cycle from an economic model in order to assess the extent to which either the high-frequency or medium-term deviation cycle is a plausible measure of the South African business cycle.

## 5.4 Plausibility of the frequency-based deviation cycle as a measure of the South African business cycle

As argued earlier, Du Plessis *et al.* (2008) construct a measure of the South African business cycle based on an econometric model in which they identify demand and supply shocks to the South African economy. Specifically, they suggest the cumulated demand shocks identified in an SVAR model is a plausible measure of the South African business cycle. In other words, these authors have a specific view of the business cycle as a demand-based phenomenon.

Figure 12 and 13 plot the high-frequency and medium-term deviation cycles with the demand-based SVAR measure for both the longer sample period (1961Q2-2006Q4) and the shorter sample period (1984Q4-2006Q4) in Du Plessis *et al.* (2008). A graphical assessment suggests that the high-frequency deviation cycle is related to the SVAR business cycle measure in the shorter sample period, but not over the longer period. The medium-term deviation cycle is not strongly related to the SVAR business cycle measure in either sample period.

As a first step, one can again calculate and compare the confidence intervals for the standard deviations of the different measures of the business cycles, as reported in Table 7:

Table 7 confirms that the standard deviation is virtually identical for the high-frequency deviation cycle and the SVAR business cycle measure over the shorter sample period, but that the confidence intervals do not overlap over the longer sample period. The high-frequency deviation cycle is therefore capturing different information to that described by the demand shocks in the SVAR model over the longer sample period. Over the shorter sample period, the high-frequency deviation cycle may yet be capturing similar information, but this will have to be confirmed by correlation analysis presented later. As far as the medium-term deviation cycle is concerned, its confidence interval clearly does not overlap with the SVAR business cycle measure in either sample period. The medium-term deviation cycle seems to be a poor approximation for a demand-based business cycle measure.

One may argue that the SVAR business cycle is not an appropriate benchmark against which to assess the information content of frequency-based cycles. South African business cycles may not be purely demand-driven. If the frequency-based cycle is capturing supply shocks in addition to demand shocks, this is a commendable rather than a problematic feature. Figure 14 and 15 compare the high-frequency and the medium-term deviation cycle with the *cumulated* demand and supply shocks suggested by the SVAR model of Du Plessis *et al.* (2008) for the period 1961-2006.

The level of variance captured by the high-frequency deviation cycle is quite different from that suggested by the cumulated SVAR shocks. This suggests that the high-frequency deviation cycle may not be an appropriate measure of the business cycle if the concept is to be extended to include some supply shocks. Table 8 repeats Table 7, but replaces the SVAR business cycle with the cumulated SVAR shocks. The medium-term deviation cycle appears to come closer to capturing similar variance to that modelled by the cumulated shocks, though the range of variance captured by the latter is still beyond that captured the former:

A comparison of volatility properties of the high-frequency and medium-term deviation cycle on the one hand and the SVAR-based measures on the other hand may shed light on the type of information content captured by frequency-based deviation cycles. However, as argued earlier, even if there is overlap in variance the series may yet behave quite differently. It is therefore necessary to consider the co-movement properties between these statistical and econometric measures of the business cycle. As noted in the study of deviation-cycle co-movement between South Africa and its major developed country trade partners, structural breaks favour rolling correlation.

Figure 16 presents these rolling correlations for both the high-frequency and medium-term deviation cycle, comparing them to the SVAR-based business cycle measure (which assumes business cycles are a demand phenomenon) and the cumulated shocks from the SVAR model (which assumes that both demand and supply shocks constitute the business cycle).

The rolling correlation estimate show that the high-frequency deviation cycle has a fairly stable

but low correlation of 0.5 with the SVAR business cycle measure. Put differently, the high-frequency deviation cycle captures information related to demand shocks, but also captures other information. This conclusion is confirmed by the rolling correlation between the high-frequency deviation cycle and the cumulated SVAR shocks, which suggest higher correlation of around 0.7 once the earlier data points of the 1960s and early 1970s are excluded. In this sense, the high-frequency deviation cycle in South Africa does not measure the business cycle, if one views the business cycle as a deviation cycle measuring demand shocks.

As far as the medium-term deviation cycle is concerned, rolling correlation with the SVAR business cycle measure is also around 0.5, although it does decline towards 0.2 during the late 1990s and then rises again. But, in general, the medium-term deviation cycle fares no worse than the high-frequency deviation cycle as a measure of a demand-based business cycle. Given the significant differences in properties of these two cycles, it is not clear how one can justify the use of a particular frequency filter to study the South African business cycle or its co-movement with other cycles. Put differently, frequency-based deviation cycles are less useful for business cycle analysis, at least in the South African context.

In contrast, the rolling correlations between the medium-term deviation cycle and the cumulated SVAR shocks are quite high, rising towards 0.9 in the more recent periods. The high correlation suggests that the medium-term deviation cycle reasonably approximates cumulative supply and demand shocks hitting the South African economy. Therefore, if one is interested in fluctuations over longer time horizons, the medium-term deviation cycle is a useful tool in the South African context.

The above conclusions have implications for the interpretation of business cycle properties, including co-movement: even if the high-frequency deviation cycle in South Africa did measure demand shocks accurately, it remains an empirical question whether the high-frequency deviation cycles in other countries are measuring similar shocks. Therefore, one cannot necessarily use correlation among high-frequency deviation cycles (or any other deviation cycle) as an indication of business cycle co-movement without also evaluating the accuracy of frequency filters in measuring specific economic shocks in each country.

## 6 CONCLUSIONS

Even if one assumes that the deviation-cycle concept is the appropriate concept for business cycle analysis, the high-frequency deviation cycle is not a sufficient measure of the South African business cycle. The paper considers the information loss by comparing the volatility and persistence properties and co-movement conclusions for the high-frequency deviation cycle and medium-term deviation cycle. Results suggest that stylized facts depend critically on the choice of frequency range. This leads to the question of what the high-frequency and medium-term deviation cycles are measuring, given that frequency-based cycles are statistical measures of the business cycle with little economic foundation. To this end, the paper compares the high-frequency and medium-term deviation cycles with demand and supply shocks identified from a structural VAR by Du Plessis *et al.* (2008). The high-frequency deviation cycle is correlated, but not highly correlated, with demand shocks and is more correlated with cumulated demand and supply shocks, which are not necessarily appropriate business cycle measures. The medium-term deviation cycle is as correlated with demand shocks, which implies that the high-frequency deviation cycle is not the more obvious choice for business cycle measurement. Given that the two cycles differ significantly in terms of volatility, persistence and co-movement, there is little to commend the use of frequency-based cycles for business cycle research in South Africa. However, the medium-term deviation cycle is highly correlated with cumulated shocks, which suggests that where medium-run investigations are concerned, the medium-term deviation cycle may be an appropriate tool.

## References

- [1] Baxter, M. and R. King (1999). "Measuring Business Cycles: Approximate Band-pass Filters for Economic Time Series." The Review of Economics and Statistics **81**(4).
- [2] Boshoff, W. H. (2005). "The properties of cycles in South African financial variables and their relation to the business cycle." South African Journal of Economics **73**(4): 694-709.
- [3] Botha, I. (2010). "A comparative analysis of the synchronisation of business cycles for developed and developing economies with the world business cycle." South African Journal of Economics **78**(2): 192-207.
- [4] Burns, A. and W. C. Mitchell (1946). Measuring Business Cycles. New York, National Bureau of Economic Research.
- [5] Canova, F. (1998). "Detrending and business cycle facts." Journal of Monetary Economics **41**: 475-512.
- [6] Christiano, L. and T. Fitzgerald (2003). "The Band Pass Filter." International Economic Review **44**(2).
- [7] Comin, D. and M. Gertler (2006). "Medium-Term Business Cycles." The American Economic Review **96**(3).
- [8] Comin, D. A., N. Loayza, et al. (2009). Medium term business cycles in developing countries. NBER Working Paper Series Working Paper 15428, <http://www.nber.org/papers/w15428>.
- [9] Croux, C., M. Forni, et al. (2001). "A measure of comovement for economic variables: theory and empirics." The Review of Economics and Statistics **83**(2): 232-241.
- [10] Du Plessis, S., B. Smit, et al. (2008). "Identifying aggregate supply and demand shocks in South Africa." Journal of African Economies **17**(5): 765-793.
- [11] Du Plessis, S. A. (2006). Business Cycles in Emerging Market Economies: A New View of the Stylized Facts. Stellenbosch Economic Working Papers 2/2006. Stellenbosch, Republic of South Africa.
- [12] Engle, R. F. and C. W. J. Granger (1987). "Cointegration and error correction: representation, estimation and testing." Econometrica **55**(2): 251-276.
- [13] Engle, R. F. and S. Kozicki (1993). "Testing for Common Features." Journal of Business and Economics Statistics **11**(4): 369-380.
- [14] Estrella, A. (2007). Extracting Business Cycle Fluctuations: What Do Time Series Filters Really Do? Staff Reports No 289. New York, Federal Reserve Bank of New York: 1-34.
- [15] Giannone, D. and L. Reichlin (2005). Euro area and US recessions, 1970-2003. Euro Area Business Cycle: Stylized Facts and Measurement Issues. L. Reichlin, CEPR.
- [16] Harding, D. and A. R. Pagan (2002). "A comparison of two business cycle dating methods." Journal of Economic Dynamics and Control **27**: 1681-1690.
- [17] Harding, D. and A. R. Pagan (2002). "Dissecting the Cycle: A Methodological Investigation." Journal of Monetary Economics **49**(2): 365-381.
- [18] Harding, D. and A. R. Pagan (2005). "A suggested framework for classifying the modes of cycle research." Journal of Applied Econometrics **20**(2): 151-159.

- [19] Hodrick, R. J. and E. C. Prescott (1997). "Postwar U.S. Business Cycles: An Empirical Investigation." Journal of Money, Credit, and Banking **29**: 1-16.
- [20] Kabundi, A. (2009). "Synchronisation between South Africa and the U.S.: a structural dynamic factor analysis." South African Journal of Economics **77**(1): 1-27.
- [21] Kabundi, A. and E. Loots (2007). "Co-movement between South Africa and the Southern African Development Community: an empirical analysis." Economic Modelling **24**: 737-748.
- [22] Laubscher, P. (2004). "The South African Economy over the 1990s and Current Prospects." Studies in Economics and Econometrics **28**(1): 21-44.
- [23] Peiró, A. (2002). "Macroeconomic synchronization between G3 countries." German Economic Review **3**(2): 137-153.
- [24] Solow, R. M. (2000). "Towards a Macroeconomics of the Medium Run." The Journal of Economic Perspectives **14**(1): 151-158.
- [25] Vahid, F. and R. F. Engle (1993). "Common Trends and Common Cycles." Journal of Applied Econometrics **8**(4): 341-360.
- [26] Zarnowitz, V. and A. Ozyildirim (2006). "Time Series Decomposition and Measurement of Business Cycles, Trends and Growth Cycles." Journal of Monetary Economics **53**(7).

**Table 1: Output data description, sources and sample periods**

Country	Series	Source	Data code	Period	Notes
SA	GDP (2005 R millions)	South African Reserve Bank (SARB)	KBP6006D	1960Q1-2010Q1	SARB data used to update 2010Q1
	GDP VOL. (2005=100)	IFS		1960Q1-2009Q4	
UK	GDP (2005 £ Million)	Office for National Statistics		1955Q1-2010Q1	ONS data used to update 2010Q1
	GDP VOL. (2005=100)	IFS		1957Q1-2009Q4	
Australia	GDP (AU\$ Millions)	Australian Bureau of Statistics	A2304402X	1959Q1-2010Q1	ABS data used to update 2010Q1
	GDP VOL. (2005=100)	IFS		1959Q1-2009Q4	
USA	GDP (2005 \$ Billions)	Bureau of Economic Analysis		1947Q1-2010Q1	
	GDP VOL. (2005=100)	IFS		1957Q1-2010Q1	
Europe	GDP (2000 US\$ Millions, fixed PPPs)	OECD	VPVOBARSA	1961Q1-2009Q4	Covers the 23 OECD European countries
	GDP VOL. (2005=100)	IFS		1998Q1-2009Q4	

**Table 2: Average medium-frequency component (as % of GDP) by decade and sample period**

	<i>1960-2010 data</i>	<i>1960-2006 data</i>	<i>1980-2010 data</i>	<i>1980-2006 data</i>
<i>1960-1969</i>	-1.95%	-2.05%	-	-
<i>1970-1979</i>	5.29%	5.34%	-	-
<i>1980-1989</i>	2.90%	3.23%	3.23%	3.36%
<i>1990-1999</i>	-6.94%	-6.92%	-5.32%	-5.25%
<i>2000-2006</i>	-1.82%	-2.83%	-1.19%	-1.33%

**Table 3: Standard deviation (%) of various frequency ranges in South Africa, with 95% confidence interval**

Component	1960Q1-2010Q1	1960Q1-2006Q4	1980Q1-2010Q1	1980Q1-2006Q4
High-frequency deviation cycle	1.52 (1.32-1.61)	1.44 (1.31-1.61)	1.47 (1.31-1.69)	1.45 (1.28-1.68)
Medium-frequency component	5.47 (4.98-6.06)	5.47 (4.98-6.11)	4.65 (4.15-5.34)	4.21 (3.73-4.88)
Medium-term deviation cycle	5.68 (5.19-6.31)	5.71 (5.20-6.37)	4.97 (4.43-5.71)	4.60 (4.07-5.33)

**Table 4: Ratio of growth to trend growth for high-frequency and medium-term deviation cycles in South Africa**

Ratio of growth to trend growth	1960Q1-2010Q1	1960Q1-2006Q4	1980Q1-2010Q1	1980Q1-2006Q4
High-frequency deviation cycle	0.40	0.40	0.41	0.40
Medium-term deviation cycle	0.16	0.16	0.07	0.07

**Table 5: Dynamic correlations (contemporaneous and lagging) of high-frequency deviation cycles in South Africa and high frequency deviation cycles in developed countries**

Type of correlation	Sample period	Australia	United Kingdom	United States	Europe
Contemporaneous (long sample)	1960Q1-2010Q1	0.46* (0.32 ; 0.60)	0.07 (-0.07 ; 0.21)	-0.12 (-0.26 ; 0.02)	0.14 (-0.00 ; 0.28)
	1960Q1-2006Q4	0.45* (0.31 ; 0.60)	-0.04 (-0.19 ; 0.11)	-0.21* (-0.36 ; -0.06)	-0.01 (-0.16 ; 0.14)
Contemporaneous (short sample)	1980Q1-2010Q1	0.49* (0.28 ; 0.67)	0.40* (0.22 ; 0.58)	0.26* (0.08 ; 0.44)	0.37* (0.19 ; 0.55)
	1980Q1-2006Q4	0.45* (0.27 ; 0.64)	0.26* (0.07 ; 0.45)	0.16 (-0.03 ; 0.35)	0.25* (0.06 ; 0.44)
Leading SA 2 quarters (long sample)	1960Q1-2010Q1	0.40* (0.26 ; 0.54)	0.26* (0.12 ; 0.40)	0.13 (-0.01 ; 0.27)	0.22* (0.08 ; 0.36)
	1960Q1-2006Q4	0.40* (0.25 ; 0.55)	0.22* (0.07 ; 0.37)	0.06 (-0.09 ; 0.21)	0.11 (-0.04 ; 0.26)
Leading SA 2 quarters (short sample)	1980Q1-2010Q1	0.38* (0.20 ; 0.56)	0.49* (0.31 ; 0.67)	0.40* (0.22 ; 0.58)	0.32* (0.14 ; 0.50)
	1980Q1-2006Q4	0.36* (0.17 ; 0.55)	0.48* (0.29 ; 0.67)	0.32* (0.13 ; 0.51)	0.12 (-0.07 ; 0.31)
Leading SA 4 quarters (long sample)	1960Q1-2010Q1	0.11 (-0.03 ; 0.25)	0.34* (0.20 ; 0.48)	0.22* (0.08 ; 0.36)	0.14 (-0.00 ; 0.28)
	1960Q1-2006Q4	0.14 (-0.00 ; 0.29)	0.41* (0.26 ; 0.56)	0.22* (0.07 ; 0.37)	0.15 (0.00 ; 0.30)
Leading SA 4 quarters (short sample)	1980Q1-2010Q1	0.05 (-0.13 ; 0.23)	0.37* (0.19 ; 0.55)	0.17 (-0.01 ; 0.35)	0.00 (-0.18 ; 0.18)
	1980Q1-2006Q4	0.07 (-0.13 ; 0.27)	0.51* (0.31 ; 0.71)	0.15 (-0.05 ; 0.35)	-0.14 (-0.34 ; 0.06)

\* Significantly different from zero at 95% confidence level

**Table 6: Dynamic correlation (contemporaneous and lagging) of medium-term deviation cycles in South Africa and medium-term deviation cycles in developed countries**

Type of correlation	Sample period	Australia	United Kingdom	United States	Europe
Contemporaneous (long sample)	1960Q1-2010Q1	0.41* (0.32 ; 0.55)	0.17* (0.03 ; 0.31)	0.17* (0.03 ; 0.31)	0.39* (0.25 ; 0.53)
	1960Q1-2006Q4	0.39* (0.31 ; 0.54)	0.01 (-0.14 ; 0.16)	0.08 (-0.07 ; 0.23)	0.27* (0.12 ; 0.42)
Contemporaneous (short sample)	1980Q1-2010Q1	0.47* (0.28 ; 0.65)	0.28* (0.10 ; 0.46)	0.35* (0.17 ; 0.53)	0.39* (0.21 ; 0.57)
	1980Q1-2006Q4	0.44* (0.27 ; 0.63)	0.07 (-0.12 ; 0.26)	0.24* (0.05 ; 0.43)	0.23* (0.04 ; 0.42)
Leading SA 2 quarters (long sample)	1960Q1-2010Q1	0.37* (0.23 ; 0.51)	0.29* (0.15 ; 0.43)	0.33* (0.19 ; 0.47)	0.35* (0.21 ; 0.49)
	1960Q1-2006Q4	0.34* (0.19 ; 0.49)	0.19* (0.04 ; 0.34)	0.26* (0.11 ; 0.41)	0.22* (0.07 ; 0.37)
Leading SA 2 quarters (short sample)	1980Q1-2010Q1	0.37* (0.19 ; 0.55)	0.37* (0.19 ; 0.55)	0.48* (0.30 ; 0.66)	0.38* (0.20 ; 0.56)
	1980Q1-2006Q4	0.33* (0.14 ; 0.52)	0.26* (0.07 ; 0.45)	0.41* (0.22 ; 0.60)	0.19 (-0.00 ; 0.38)
Leading SA 4 quarters (long sample)	1960Q1-2010Q1	0.08 (-0.06 ; 0.22)	0.26* (0.12 ; 0.40)	0.20* (0.06 ; 0.34)	0.14 (-0.00 ; 0.28)
	1960Q1-2006Q4	0.06 (-0.09 ; 0.21)	0.26* (0.11 ; 0.41)	0.18* (0.03 ; 0.33)	0.09 (-0.06 ; 0.24)
Leading SA 4 quarters (short sample)	1980Q1-2010Q1	0.01 (-0.17 ; 0.19)	0.20* (0.02 ; 0.38)	0.17 (-0.01 ; 0.35)	-0.01 (-0.19 ; 0.17)
	1980Q1-2006Q4	-0.03 (-0.23 ; 0.17)	0.21* (0.01 ; 0.41)	0.15 (-0.05 ; 0.35)	-0.15 (-0.35 ; 0.05)



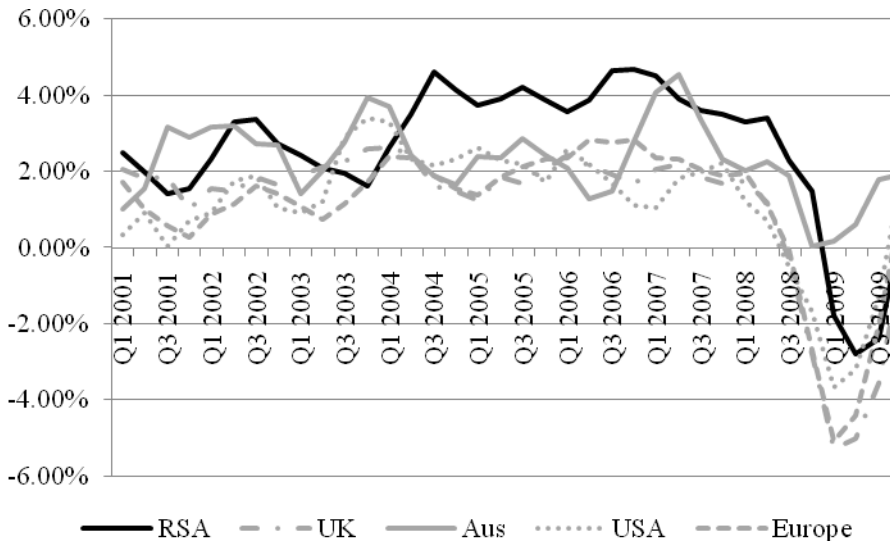
**Table 7: Standard deviation (%) of various frequency ranges and the SVAR business cycle in South Africa, with 95% confidence interval**

<b>Component</b>	<b>1961Q2-2006Q4</b>	<b>1984Q4-2006Q4</b>
High-frequency deviation cycle	1.46 (1.33-1.63)	1.28 (1.11-1.50)
Medium-term deviation cycle	5.60 (5.08-6.25)	3.75 (3.27-4.40)
SVAR business cycle	2.25 (2.05-2.52)	1.28 (1.11-1.50)

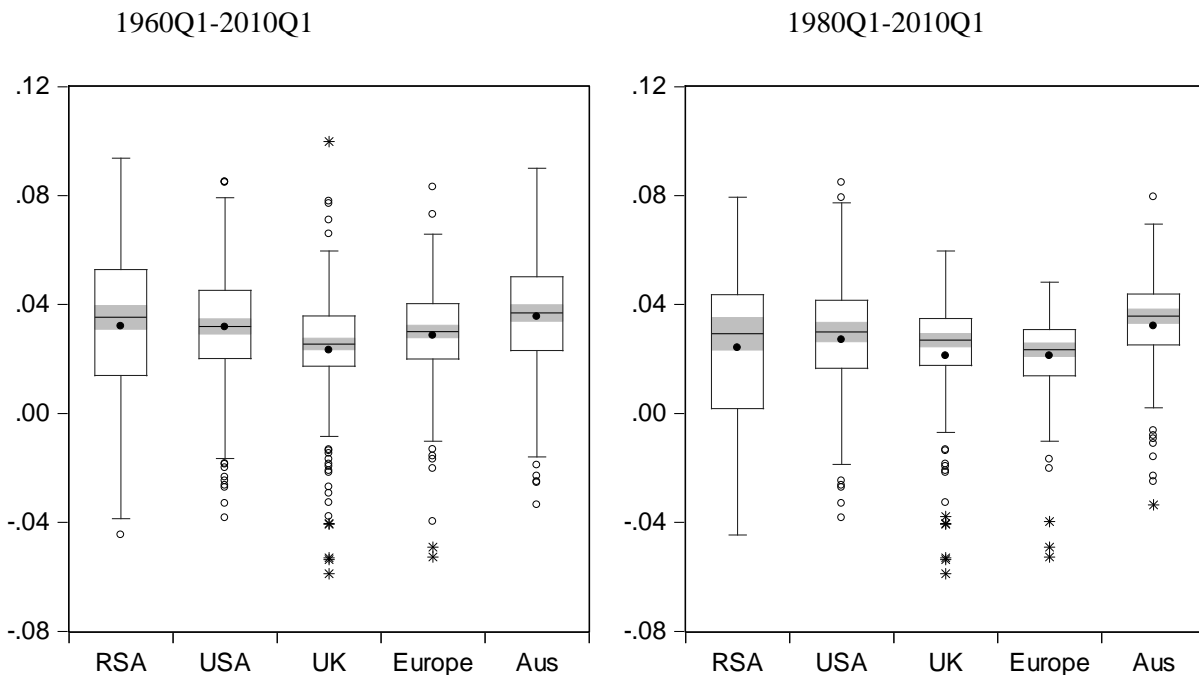
**Table 8: Standard deviation (%) of various frequency -ranges and the cumulated SVAR shocks in South Africa, with 95% confidence interval**

<b>Component</b>	<b>1961Q2-2006Q4</b>
High-frequency deviation cycle	1.46 (1.33-1.63)
Medium-term deviation cycle	5.60 (5.08-6.25)
SVAR cumulated demand and supply shocks	8.61 (7.81-9.59)

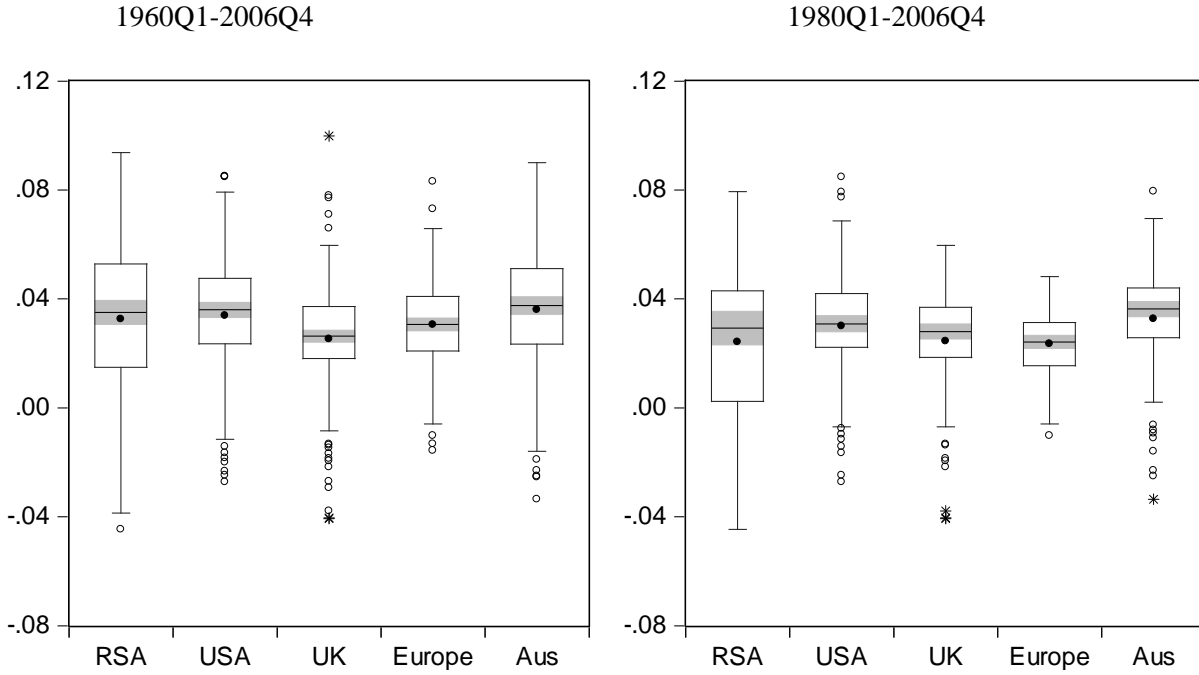
**Figure 1: Real output growth (year-on-year) in South Africa and developed countries, 2001Q1-2009Q4**



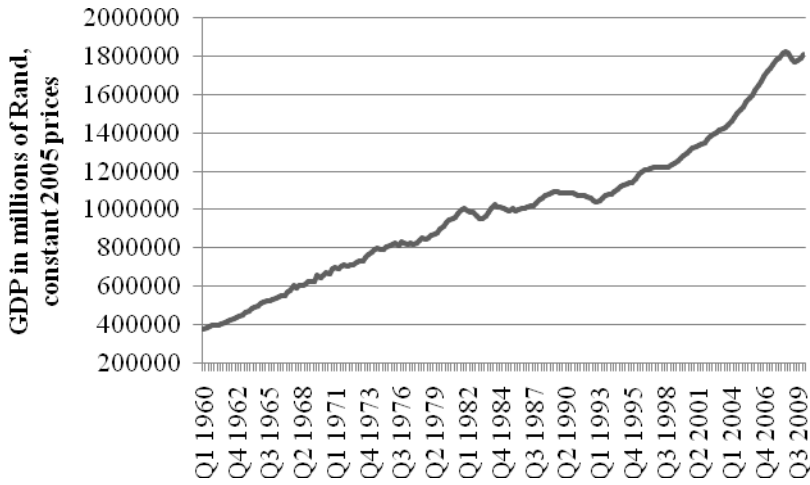
**Figure 2: Box-and-whisker plots for output growth, including post-2006 data**



**Figure 3: Box-and-whisker plots for output growth, excluding post-2006 data**

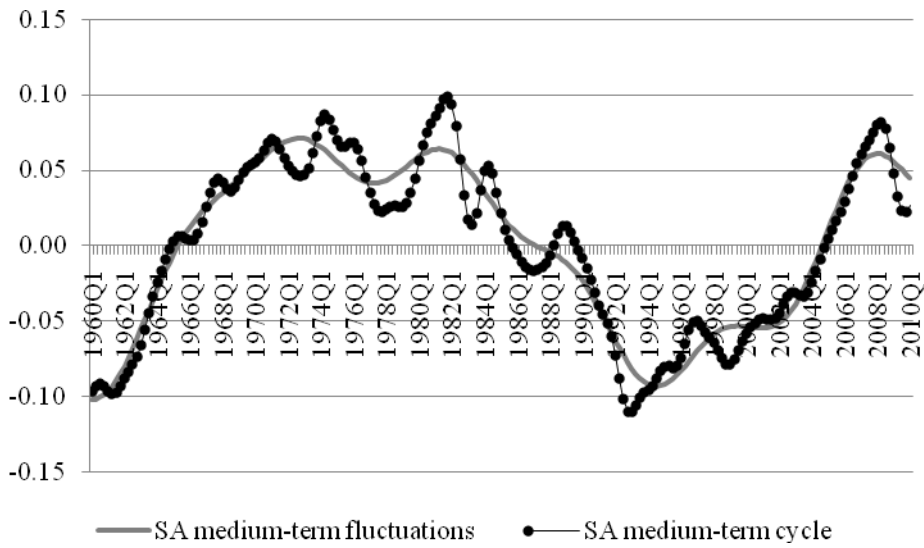


**Figure 4: Real GDP in South Africa, 1960Q1-2010Q1**

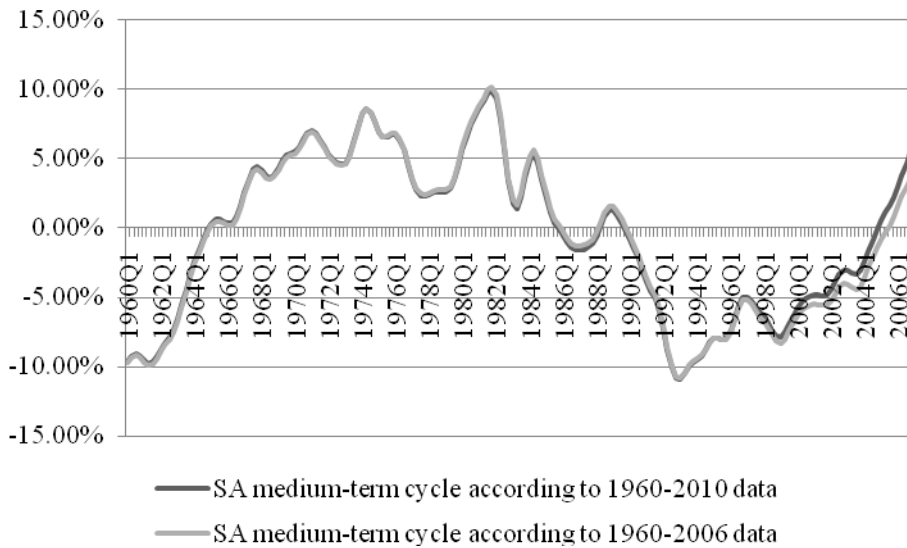


Source: South African Reserve Bank (2010)

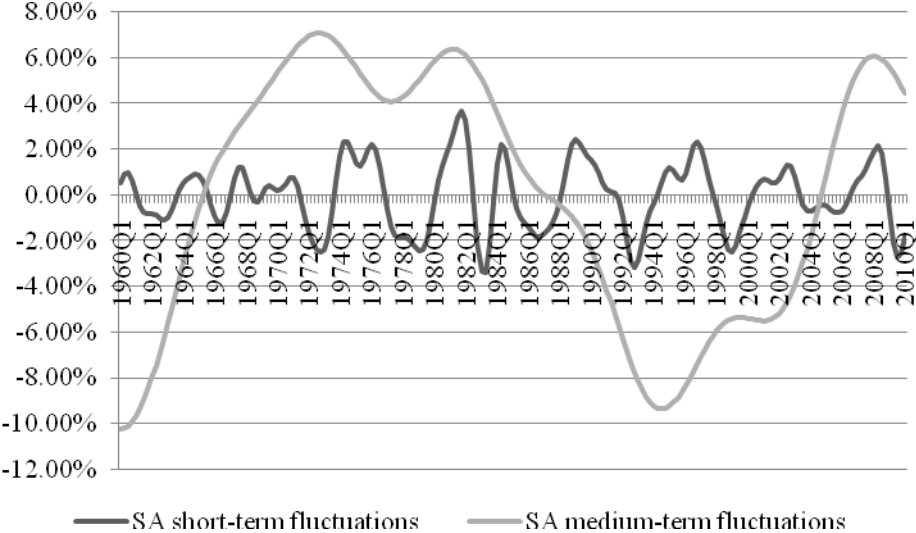
**Figure 5: The medium-term deviation cycle in South Africa, 1960Q1-2010Q1**



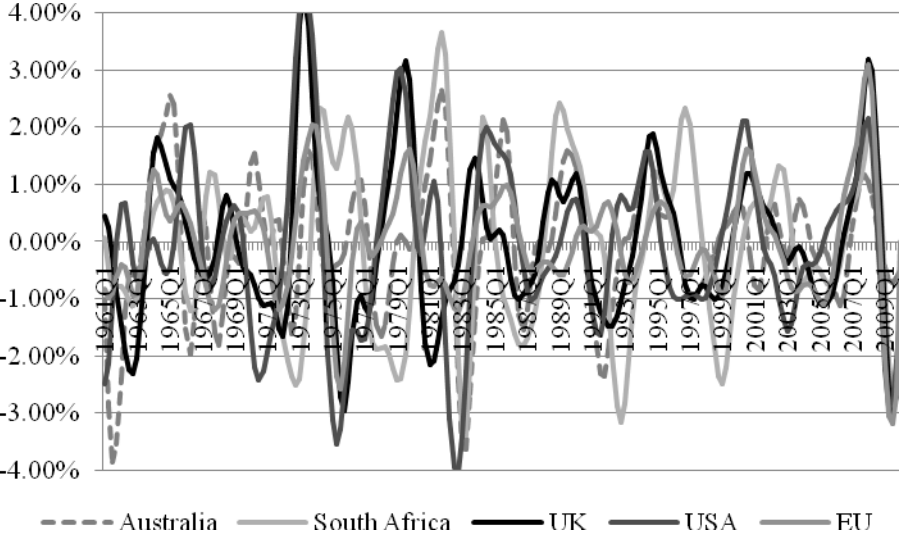
**Figure 6: The medium-term deviation cycle in South Africa, 1960Q1-2006Q4, calculated on datasets including and excluding financial crisis period**



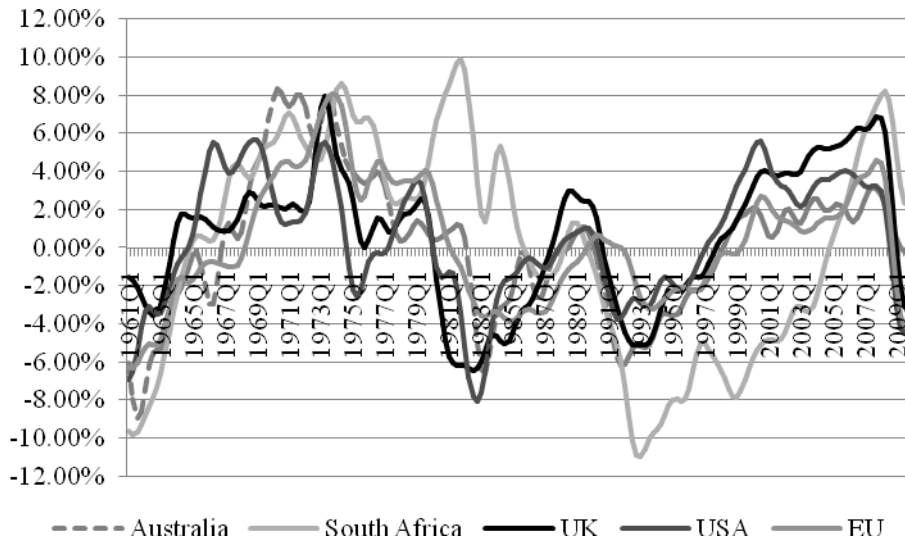
**Figure 7: The medium-term deviation cycle compared to the high-frequency deviation cycle in South Africa, 1960Q1-2010Q1**



**Figure 8: High-frequency deviation cycles in South Africa, USA, UK, Europe and Australia, 1960Q1-2010Q1**

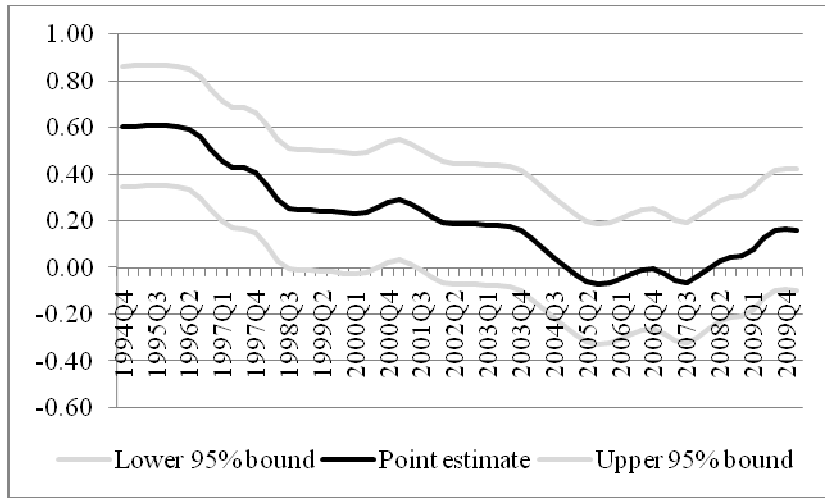


**Figure 9: Medium-term deviation cycles in South Africa, USA, UK, Europe and Australia, 1960Q1-2010Q1**

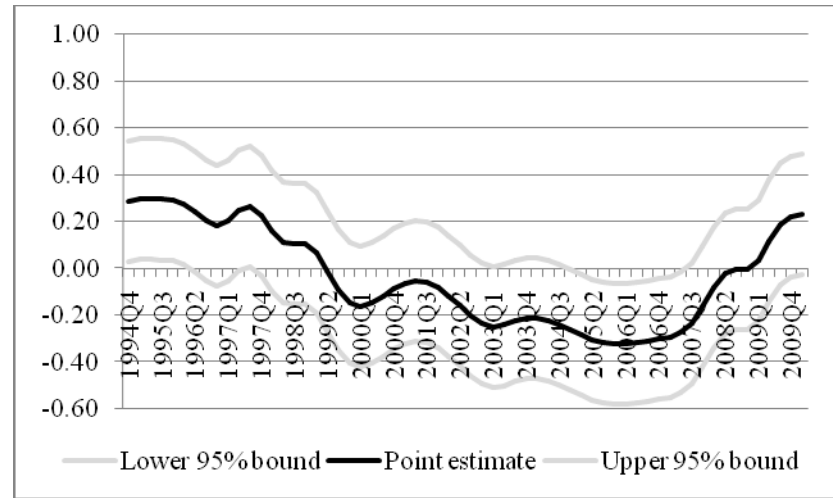


**Figure 10: Rolling correlations between high-frequency deviation cycles in South Africa and developed countries, 1980Q1-2010Q1**

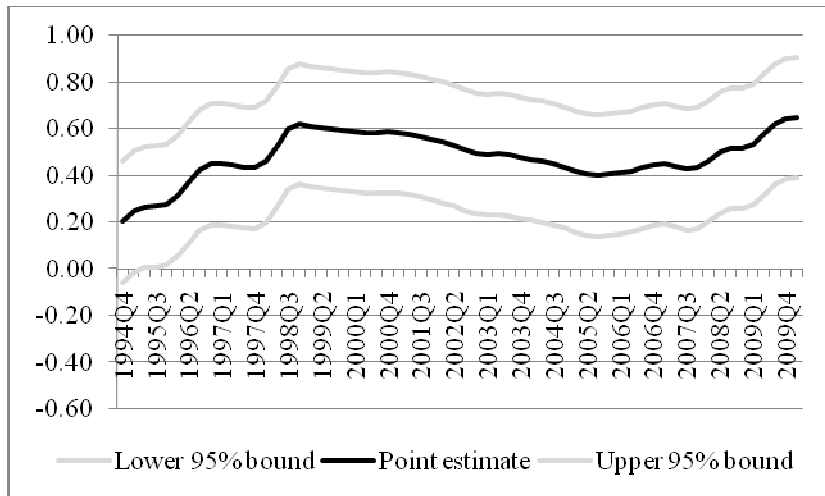
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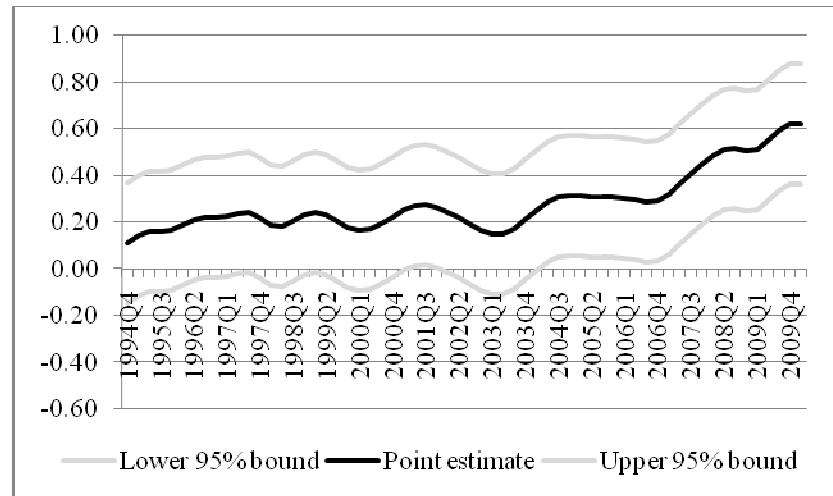
United States



United Kingdom

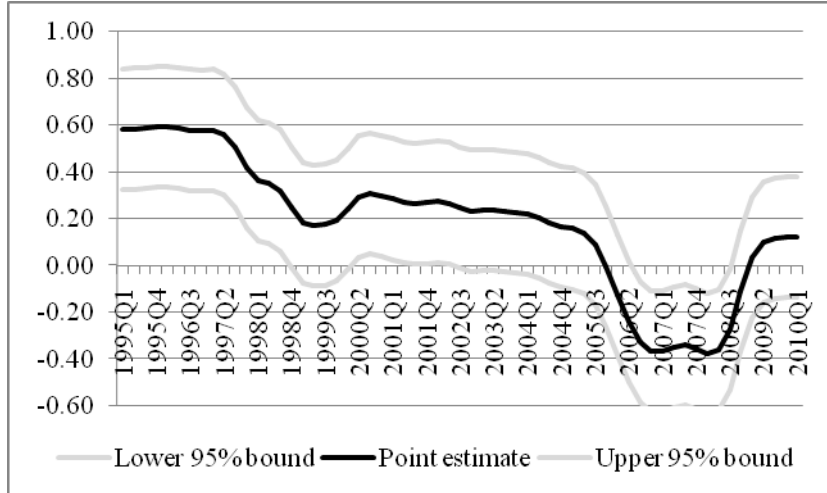


Europe

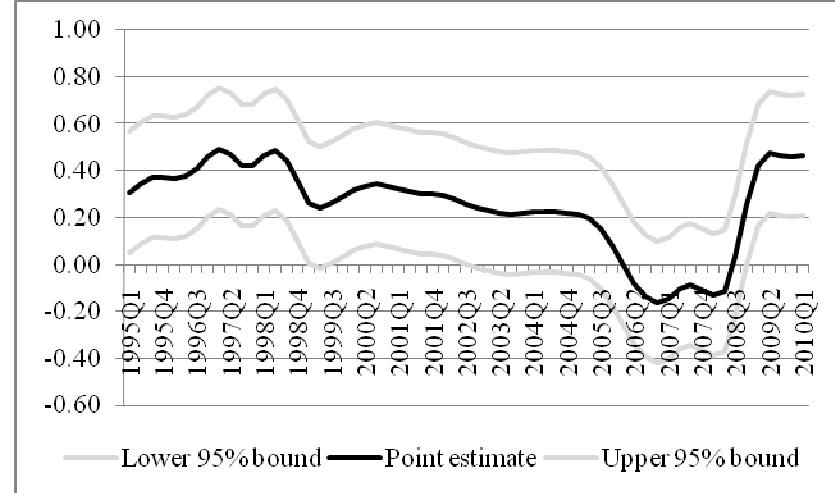


**Figure 11: Rolling correlations between medium-term deviation cycles in South Africa and developed countries, 1980Q1-2010Q1**

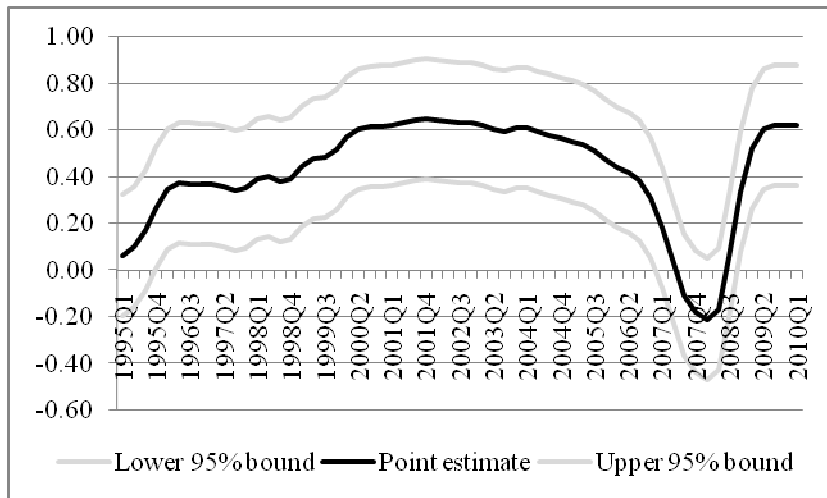
Australia



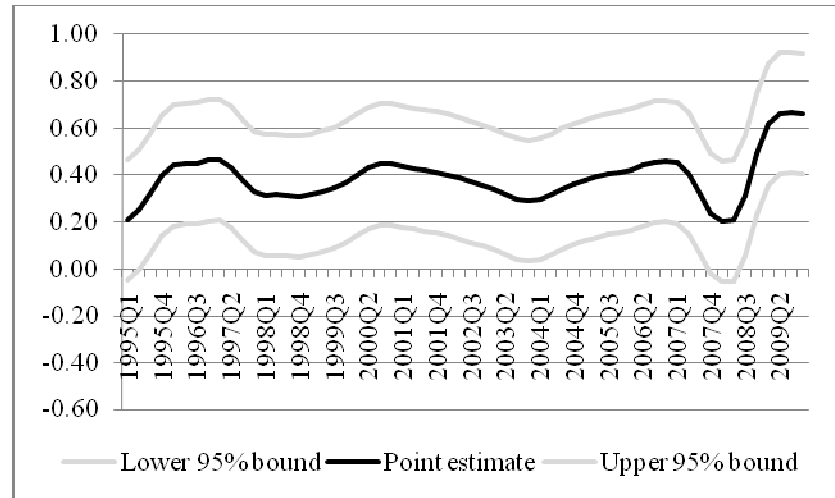
United States



United Kingdom

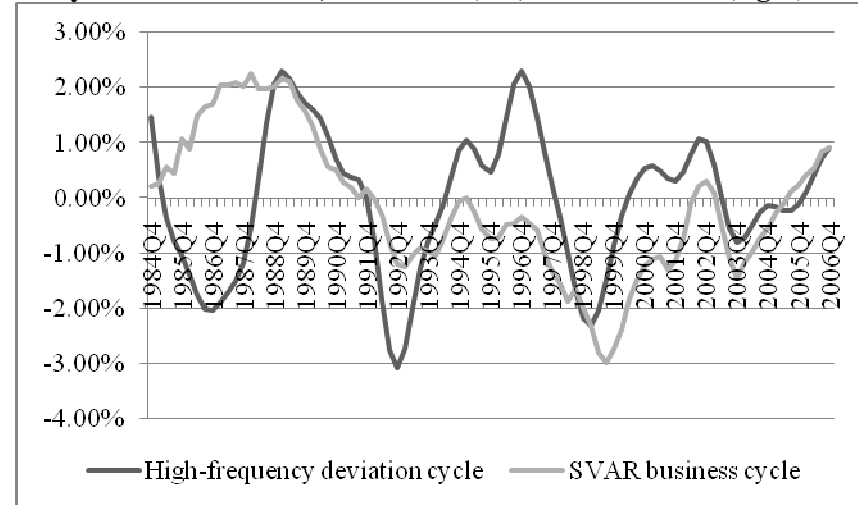
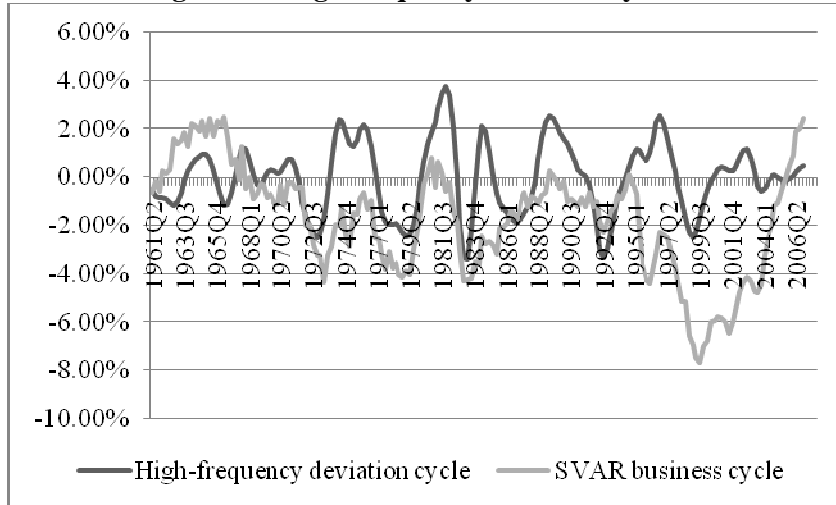


Europe

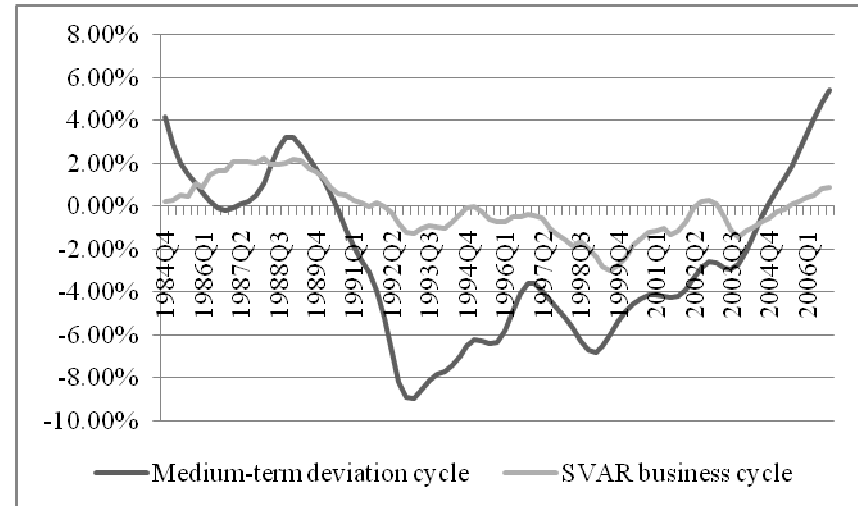
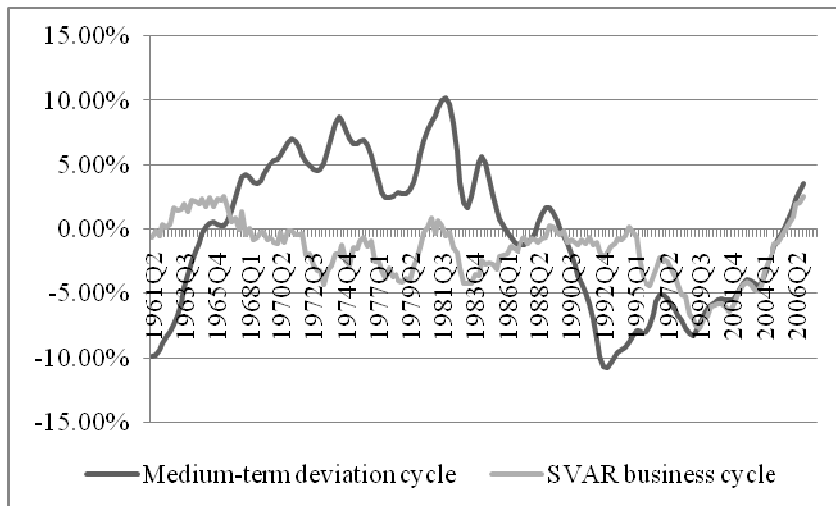




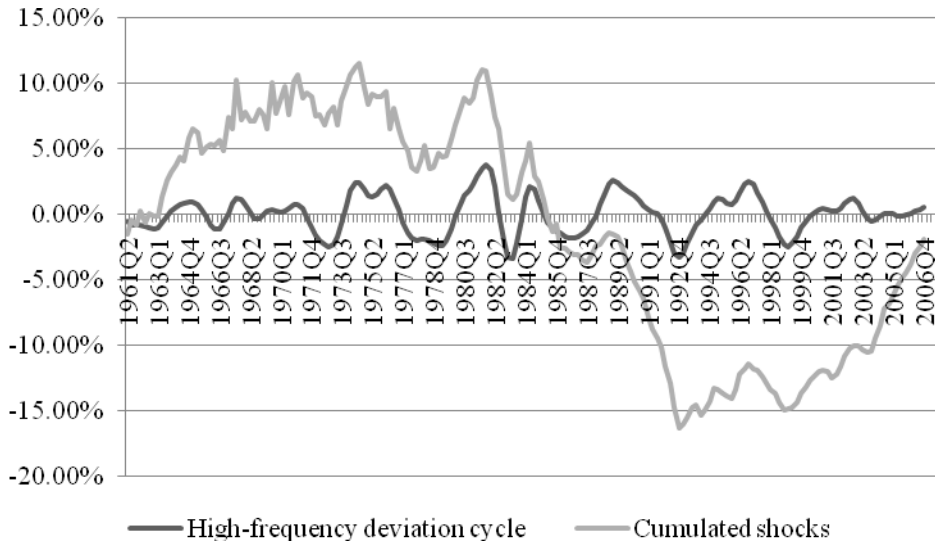
**Figure 12: High-frequency deviation cycle and SVAR business cycle in South Africa, 1961-2006 (left) and 1984-2006 (right)**



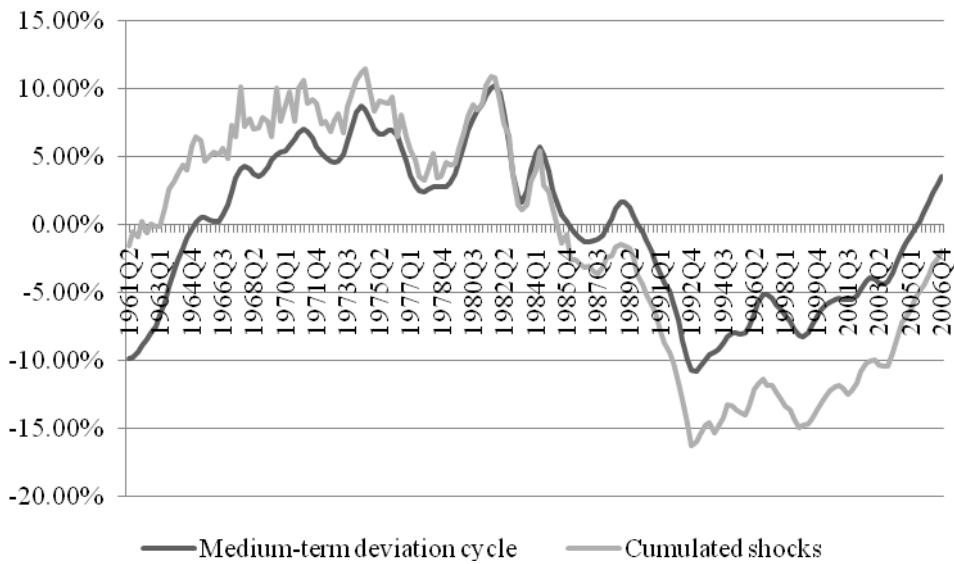
**Figure 13: Medium-term deviation cycle and SVAR business cycle in South Africa, 1961-2006 (left) and 1984-2006 (right)**



**Figure 14. High-frequency deviation cycle and cumulated SVAR shocks, 1961-2006**

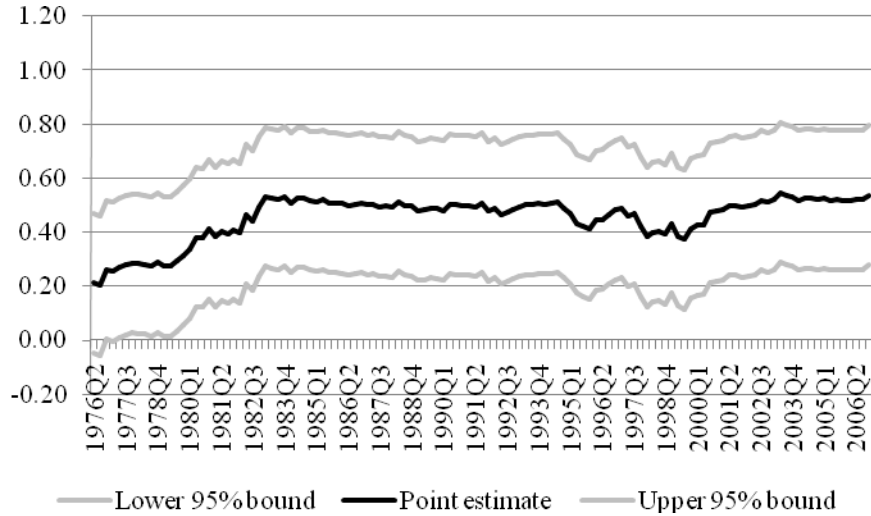


**Figure 15. Medium-term deviation cycle and cumulated SVAR shocks, 1961-2006**

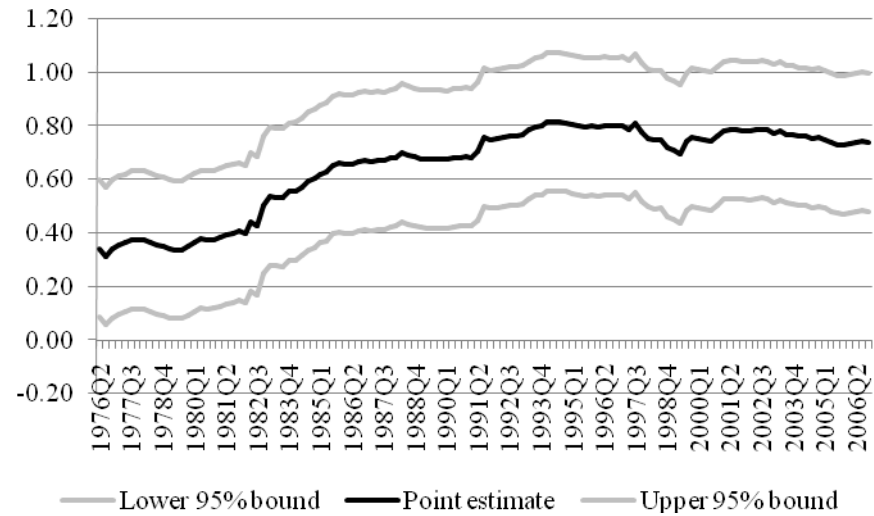


**Figure 16: Rolling correlations between deviation cycles and SVAR-based measures in South Africa, 1961Q2-2006Q4**

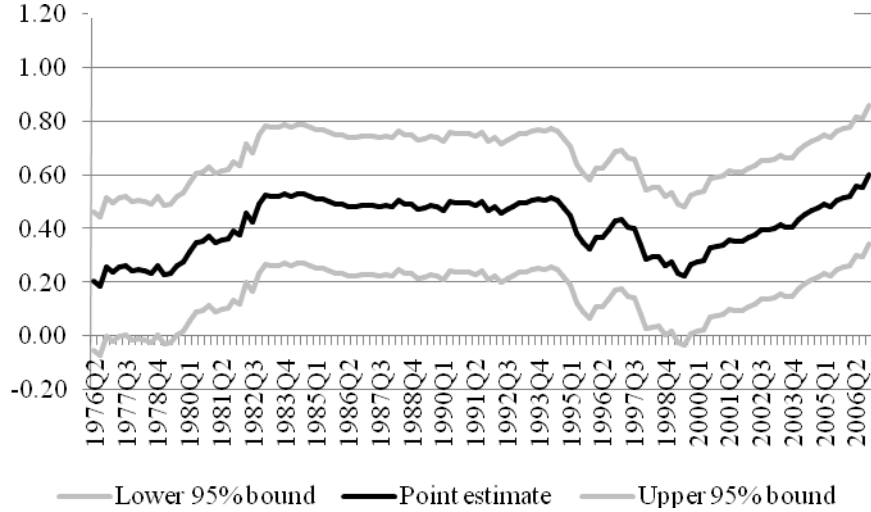
*High-frequency deviation cycle and SVAR business cycle*



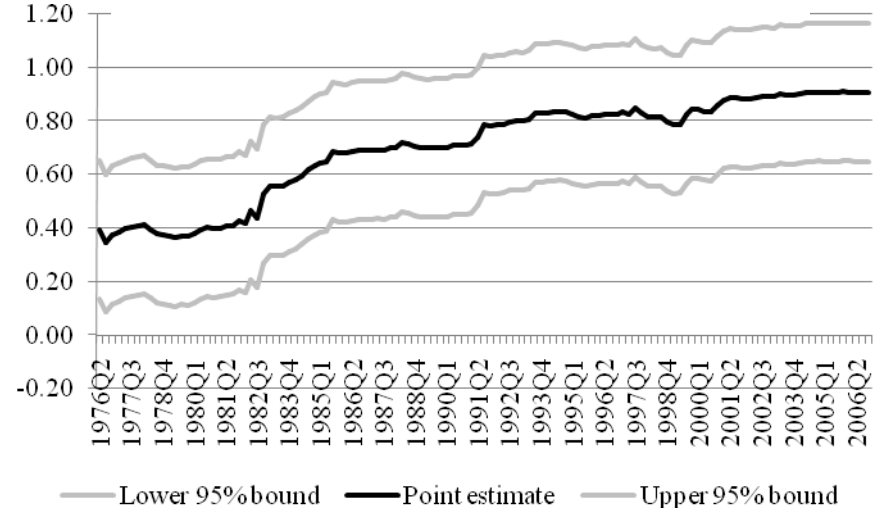
*High-frequency deviation cycle and cumulated SVAR shocks*



*Medium-term deviation cycle and SVAR business cycle*



*Medium-term deviation cycle and cumulated SVAR shocks*



APPENDIX

Figure A1: Medium-term cycle in the USA

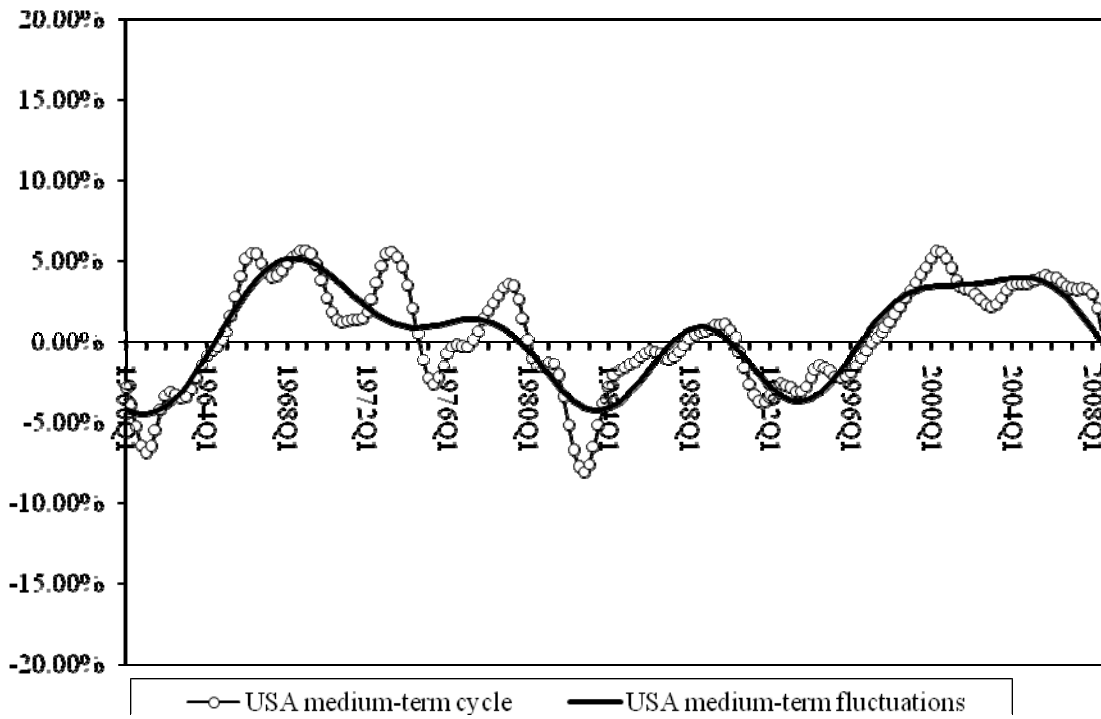


Figure A2: Medium-term cycle in the UK

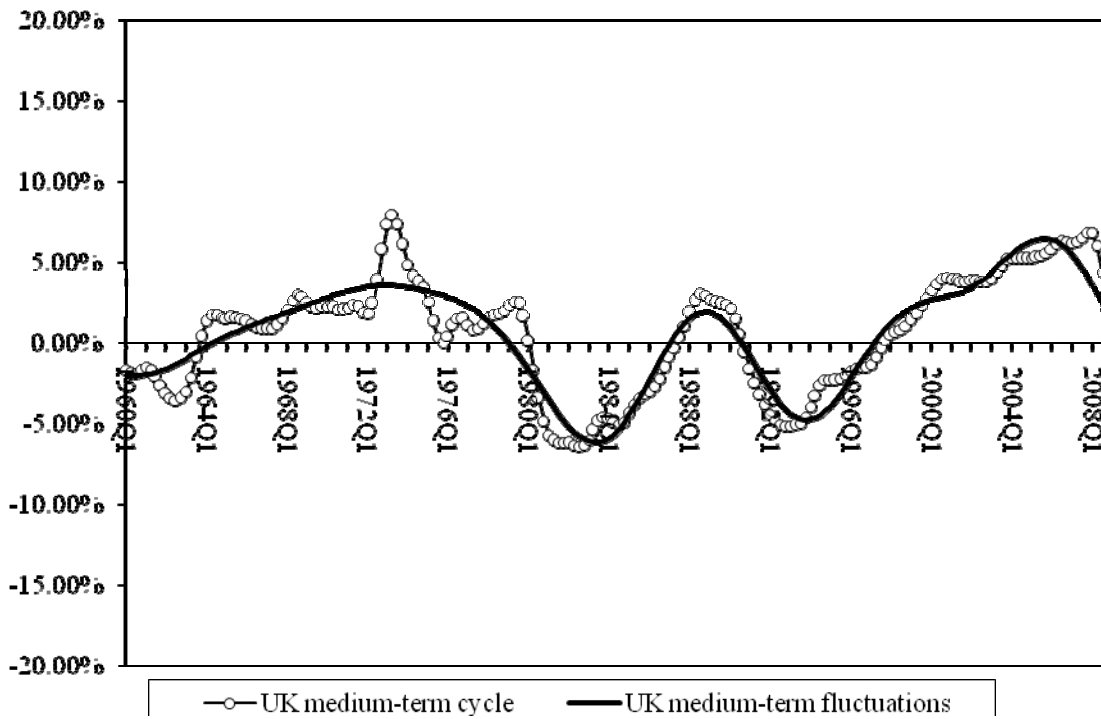


Figure A3: Medium-term cycle in Europe

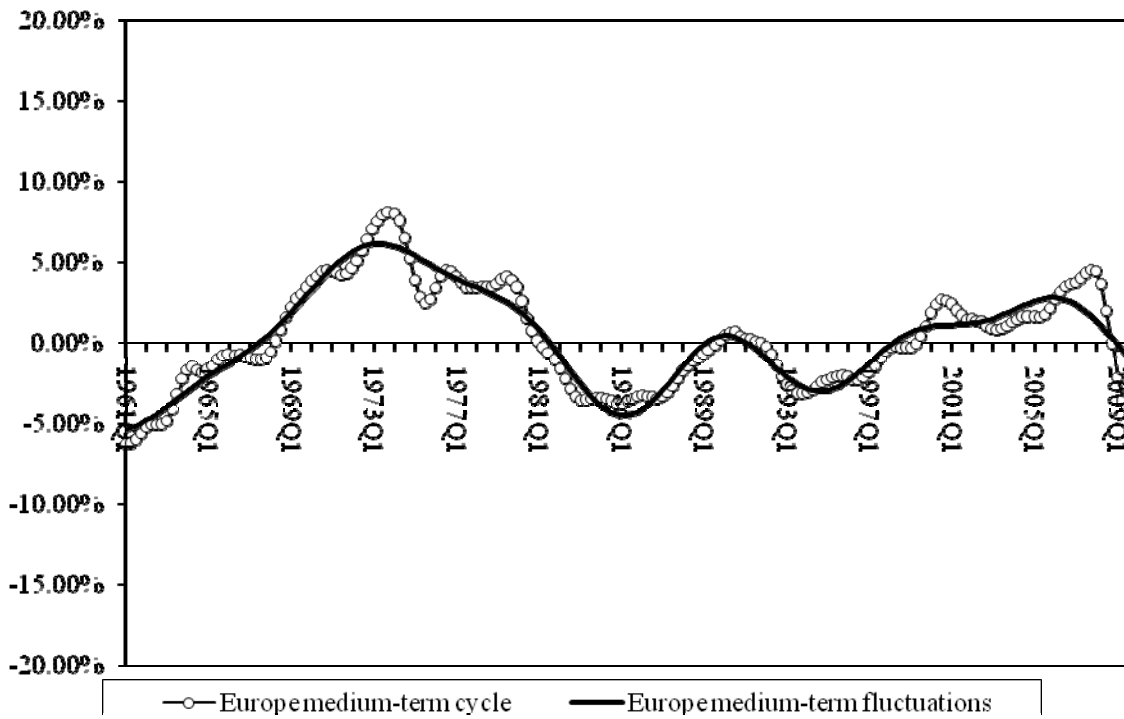


Figure A4: Medium-term cycle in Australia

