# Business Sentiment and the Business Cycle in South Africa

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**ABSTRACT**

The South African Reserve Bank's composite coincident and leading indicators are key inputs in the Bank's elaborate process for identifying business cycle turning points in South Africa. This data-intensive process has drawback, in that there is a significant delay in both the publication of the indicators and in the determination of the official turning points. We show that business confidence indicators (BCIs), published by both the Bureau for Economic Research (BER) at Stellenbosch University and the South African Chamber for Commerce and Industry (SACCI), can be useful, timely and robust indicators of the South African business cycle. The two BCIs, and the BER BCI in particular, are useful leading indicators of turning points in the South African business cycle and track the official business cycle relatively closely, while they are published before the official series and are not subject to revision. The BCIs also contain relevant information for the prediction of output growth. We also review a recession-prediction algorithm of the BER, relying on six variables (including the BER BCI), which has proven successful at dating South African business cycle recessions.

**KEYWORDS**

Business cycles, Business confidence, Sentiment, Leading indicators, Turning points

## 1 Introduction

Central banks across the world, including the South African Reserve Bank (SARB), rely on an elaborate methodology based on the analysis of a large number of lagging, coincident and leading indicators to determine business cycle turning points. This methodology is characterised by significant time delays in the publication of turning points (Lehohla & Morudu, 2011). Consequently, other institutions, including the Bureau for Economic Research (BER) at Stellenbosch University, also publish leading indicators. This paper reviews these alternative indicators of the South African business cycle, with an emphasis on the business confidence index of the BER as a potentially useful, timely and robust leading indicator of the South African business cycle.

[1] This work forms part of a contribution to a new book on business cycles in the BRICS countries.

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## 2 Challenges in Relying on the SARB Business Cycle Indicators

It is important to note that the SARB determines turning points in terms of the growth cycles, which represent fluctuations around the long-term growth trend in activity. In this paper the business cycle refers to the cycle in real economic activity, measured either as a growth cycle or as a classical cycle. We use the term “downswing” to refer to the growth cycle downswing phases and the term “contraction” to refer to classical business cycle contractions (recessions).

The SARB determines turning points in the South African business cycle based on an analysis of composite leading, coincident and lagging business cycle indicators (see Venter (this volume) and Venter (2005a)). Composite business cycle indicators are compiled by integrating various individual economic indicators into a single time series, which mirrors the movement of, and the turning points in, the business cycle (Van der Walt & Pretorius 2004).

A significant drawback of the SARB methodology is the significant delay involved in both the publication of the indicators and the determination of the official turning point dates. The SARB publishes the composite leading indicator monthly, but only six to eight weeks after the reference month. When the composite leading indicator began declining in August 2006, initial estimates became available around October 2006 and only become final around January 2007, which represents a five-month lag. In December 2007, which turned out to be the official peak date, the SARB dating committee was still considering a very moderate decrease in the leading indicator from June to July 2007. This substantial delay limits the usefulness of the indicators in terms of business forecasting and policy formation (Lehohla & Morudu, 2011).

Delays in the determination of official business cycle turning points are even more extensive. As South African business cycles are determined as deviations from a long-term trend, turning points are only confirmed after a significant delay. During the extended expansion phase from September 1999 to November 2007, the composite coincident indicator exhibited two short periods of decline: during the first half of 2001 and again during the first half of 2003. As reference turning points are not subject to revision, the investigation of these two potential downswing phases was delayed until 2005, when a consistent data set became available. The official business cycle peak in December 2007 was announced in September 2009, almost two years after the fact.

Outside users aiming to predict cyclical conditions do not usually have access to or participate in the SARB’s elaborate process of identifying turning points, which creates room for error when relying solely on the SARB’s coincident or leading indicator to identify cycles. In light of these challenges, it remains important to consider alternative indicators that are timely and that may complement the official composite indicators. In South Africa, the BER has done important work in developing alternative indicators of cyclical activity based on business confidence and in developing other composite approaches to identifying turning points.

The academic literature, too, has explored the potential role that specific variables can play. The following section provides a brief review of the academic literature on South Africa. The subsequent section presents new empirical evidence on the performance of business confidence indicators in predicting cyclical activity in South Africa. The final section then reviews the performance of an alternative algorithm, also developed at the BER, for the prediction of downswing phases in South Africa.

# 3 Selected Academic Results on Business Cycle Indicators in South Africa

Academic research over the past fifteen years has sought to identify individual variables, often from the financial markets, that could improve on the performance of the SARB's composite leading indicator. The findings in this literature can be summarized along two lines. Firstly, the South African literature, consistent with the SARB, BER and indeed most of the international literature, finds predictive power for the yield curve in dating recessions (see Moolman (2004), Boshoff (2005), Khomo & Aziakpono (2007), Clay & Keeton (2011), Botha & Keeton (2014)). Secondly, Moolman (2003) finds evidence that short-term interest rates outperform both the SARB's composite leading indicator and the yield curve, with an average lead time of 7 months. In particular, Moolman finds that the SARB's leading indicator has a consistent lead of only 4-5 months, which, given the lag in publication, renders the indicator less useful for pure forecasting purposes.

Even if other variables may outperform the leading indicator as an isolated variable for predicting cyclical turning points, academic research supports the SARB's data-rich approach to business cycle identification – where the composite leading indicator forms part of a larger assessment. Recent work by researchers at the SARB, Bosch & Ruch (2013), finds support for a data-rich approach at their institution.

# 4 Business Confidence as Leading Indicator in South Africa

## 4.1 Business confidence indices by BER and SACCI

Business confidence indicators have predictive power for economic growth and are often accurate leading indicators of business cycle turning points (Taylor & McNabb (2007); Gupta & Kabundi (2011)). Even if the unique information content of business confidence indicators is limited, the timeliness of these survey-based indicators renders them useful for monitoring and predicting economic activity (Gayer et al. (2014); Kabundi et al. (2016)).

Two indicators of business confidence are published regularly in South Africa: the BER Business Confidence Index (BER BCI) and the South African Chamber of Commerce and Industry Business Confidence Index (SACCI BCI). The BER BCI, in particular, has proven useful both as a predictor of economic growth and as a leading indicator of turning points in the South African business cycle. Indeed, it is one of twelve leading indicator series relied on by the SARB when determining the official turning points.

The BER BCI is constructed from the BER's quarterly business tendency surveys, which are similar to surveys such as the European Commission business tendency surveys, the German Ifo Business Climate Survey and the Federal Reserve Bank of Philadelphia's Business Outlook Survey. The BER BCI is constructed from a specific question that appears in all of the sectoral surveys: "*Are prevailing business conditions: Satisfactory, Unsatisfactory?*" The BCI is the weighted percentage of respondents that rated prevailing business conditions as "*Satisfactory*". The responses are weighted using firm size (turnover) and subsector weights. The confidence indicator reflects a rating of business conditions at a specific point in time (see Kershoff (this volume)).

The SACCI BCI is a composite monthly index of thirteen quantitative sub-indices thought to have the greatest bearing on the prevailing 'mood' of South African business. These include the exchange rate, inflation, the prime rate, retail sales volumes, credit extension, commodity prices, import and export volumes, new vehicle sales, utility services, manufacturing production, building plans passed, and the stock market index. Therefore, the SACCI BCI is an *ex post* measure of actual activity, based on the assumption that recent business activity is indicative of the extent of business confidence (SACCI, 2011).

The BCIs enjoy some advantages over the SARB's composite indicators for the purpose of identifying and predicting turning points. The BCIs are available well in advance of official statistics, such as the leading and coincident indicators, as well as GDP. The BER BCI and the SACCI BCI are published four and two weeks, respectively, before the end of the reference quarter, which is approximately two months prior to the first official GDP estimates (Kershoff, 2000). The composite coincident indicator, in contrast, is published six to eight weeks after the reference month. Even if the BCIs have a coincident relationship with GDP, their early availability implies that they would still be quasi-leading indicators. The survey-based BER BCI also avoids trend and seasonality problems often encountered with composite indicators (ECB, 2013). A drawback of the BER BCI is that it is only available at a quarterly frequency, whereas the coincident, leading and SACCI indicators are available at a monthly frequency.

The following section illustrates the usefulness of these BCIs, both as leading indicators of business cycle turning points and for forecasting real GDP growth, and compares these to the SARB's leading and coincident indicators.

### 4.2 Empirical Results

#### *4.2.1 Correlations*

Figure 1 illustrates the quarterly BER BCI, as well as the growth rates of the quarterly versions of the SACCI BCI and the SARB's leading and coincident indicators. Growth rates are used to remove unit roots and are calculated as annual quarter-on-quarter growth rates, e.g. 2015Q1 over 2014Q1. Downswing phases are shaded and the indicators are standardised for plotting. The SACCI BCI is only available from 1991Q4. The BCIs track the official business cycle turning points reasonably well and appear to be correlated with the two official composite indicators.

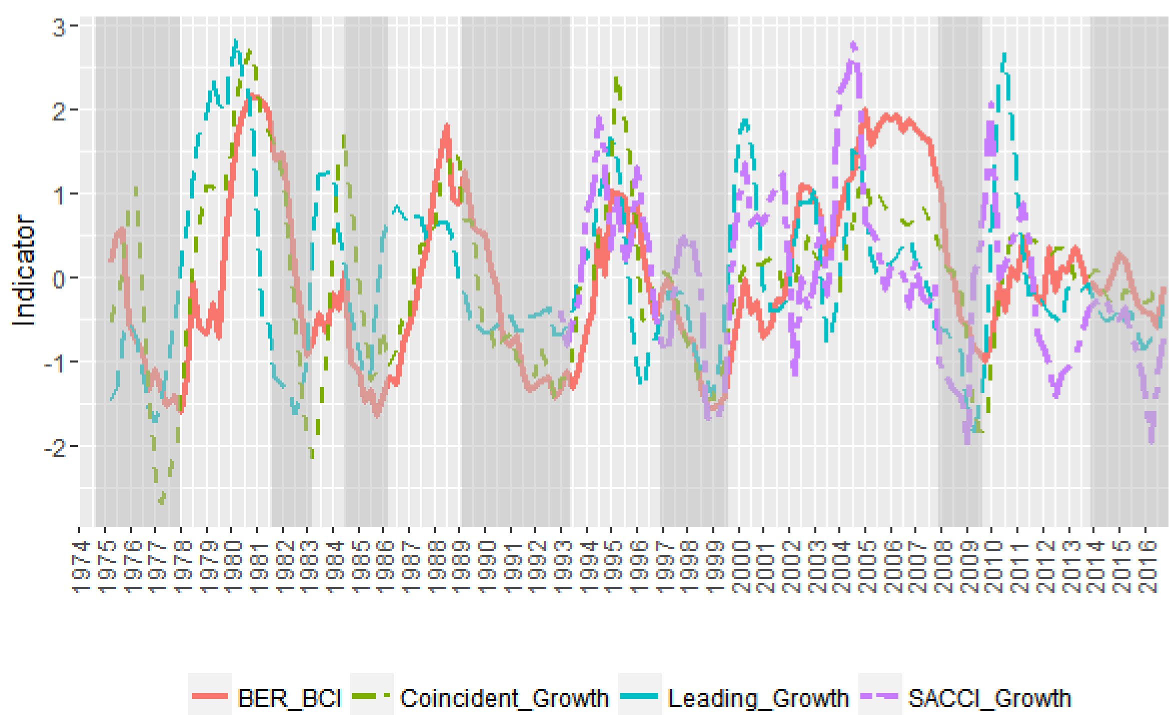



**Figure 1. BCIs and the leading and coincident indicators compared to downswing phases (shaded)**

The tracking record of the indicators is measured by their correlation with the corresponding reference series. Table 1 reports the contemporaneous correlations of the annual quarter-on-quarter growth in real GDP and the growth rates in the quarterly indicators (illustrated in Figure 1). All the indicators exhibit a significant positive correlation with real GDP growth. The correlation between real GDP growth and the coincident indicator growth rate (0.71) is the same as the correlation between real GDP growth and the BER BCI (0.71).

**Table 1. Contemporaneous correlations between the indicators and real GDP growth**

| | RGDP Growth | Coincident Growth | Leading Growth | BER BCI |
|---|---|---|---|---|
| **Coincident Growth** | 0.71*** | | | |
| **Leading Growth** | 0.32*** | 0.50*** | | |
| **BER BCI** | 0.71*** | 0.76*** | 0.31*** | |
| **SACCI Growth** | 0.20* | 0.27*** | 0.49*** | 0.29*** |

*Note: *p<0.1; **p<0.05; ***p<0.01*

Figure 2 illustrates the cross-correlograms for the indicators and real GDP growth, which help to unpack the dynamic relationships. All the indicators exhibit relatively high correlations with real GDP growth. The leading indicator and the SACCI BCI exhibit the highest correlation statistics with 3-quarter lagged real GDP growth. The results imply that the BER BCI, in particular, is a potentially useful leading or quasi-leading indicator and may contain predictive information for real economic activity.

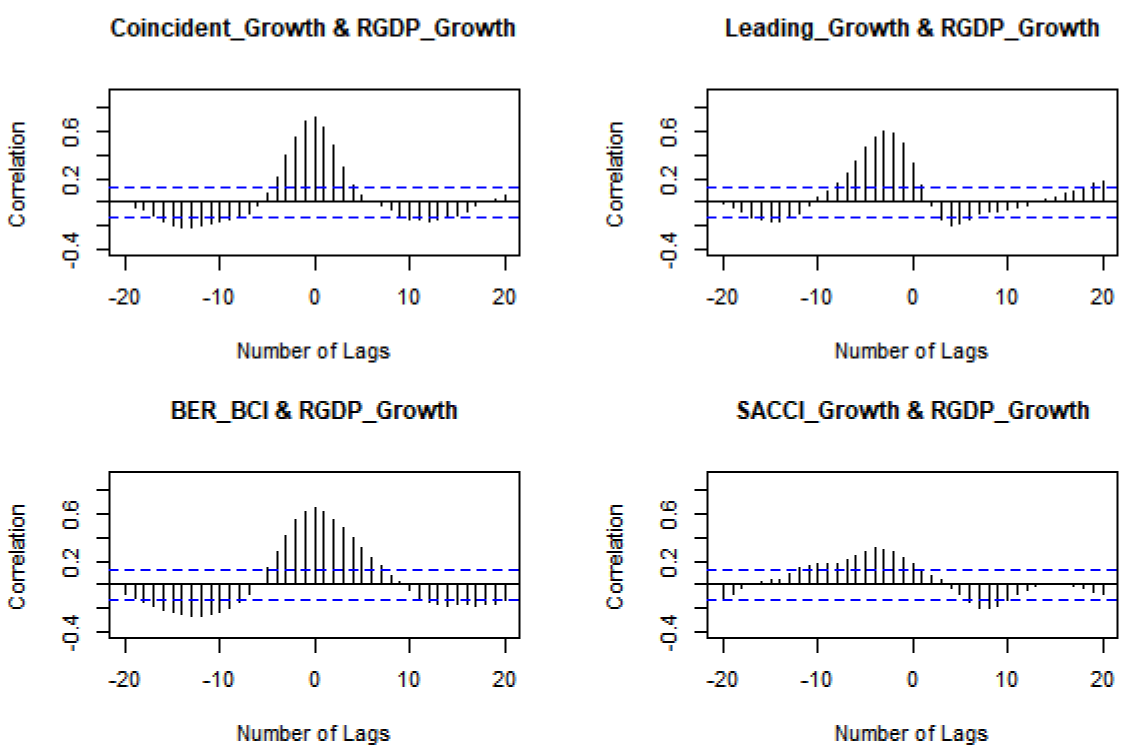
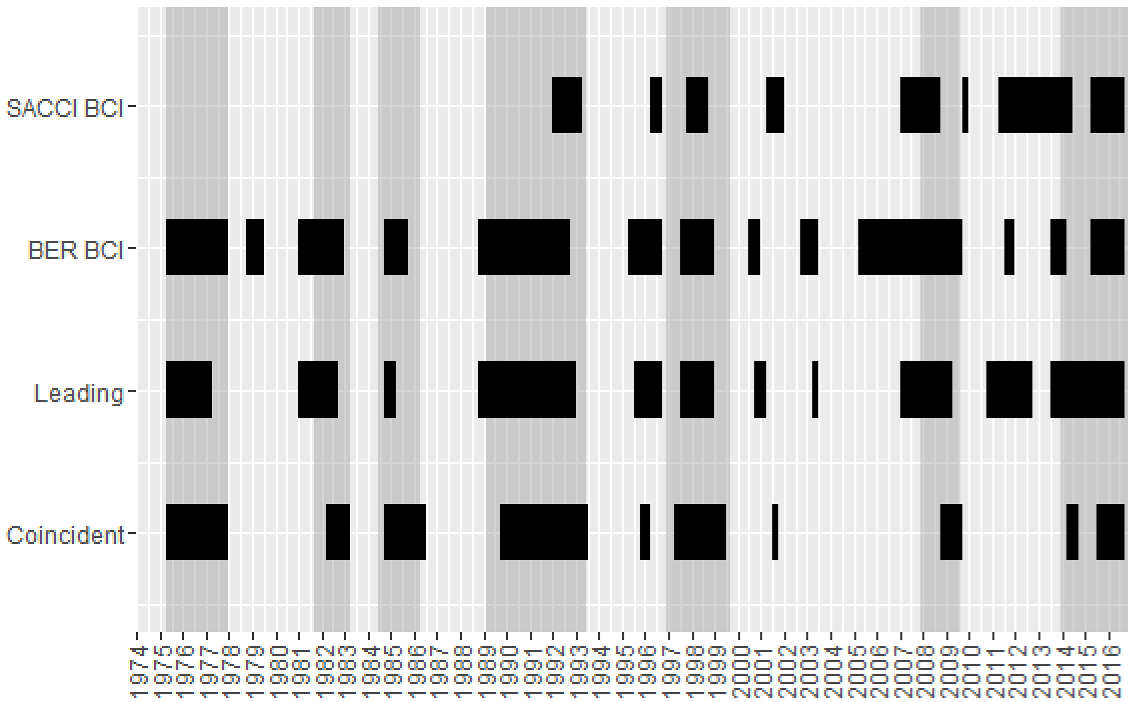



**Figure 2. Cross-correlograms of indicators and real GDP growth**

### *4.2.2 Leading indicator properties*

While correlation statistics offer information about the general conformity of two economic series, they are of limited use when evaluating the leading indicator properties of a potential indicator. For one, unit roots in the SARB indicators require correlation calculations to be performed on growth rates, which represent a growth rate cycle compared to classical cycles in the levels of an indicator.

Furthermore, an accurate leading indicator should not only conform to economic activity in general (as reflected in high correlation statistics), but should also have turning points that match consistently with those of the reference cycle (Boshoff, 2005). Therefore, an evaluation of the BCIs as leading indicators requires investigating whether turning points in the levels of BCIs consistently lead, coincide with, or lag peaks and troughs of the official business cycle.




*Notes: Black rectangles indicate the contractionary periods for a particular indicator. Grey columns indicate the official SARB downswing periods. The SACCI BCI is only available from 1991Q4.*

**Figure 3. Indicator turning points compared to the official SARB turning points**

This paper determines turning points in the levels of the official indicators and the BCIs (i.e. classical cycles), using the BBQ method, with the censoring rule suggested by Harding & Pagan (2002). The resulting phases are illustrated in Figure 3. The black rectangles show the contractionary phases identified for each indicator, while the grey columns indicate the official SARB downswing phases. Figure 3 therefore compares contractions in the classical cycles of the indicators to the official SARB downswing phases based on growth cycles. Du Plessis (2006) showed that the official SARB growth cycle and the classical cycle, identified with the BBQ method, were highly synchronised.

The sample period (from 1975Q1 to 2016Q3) contains 6 official upswing phases and 7 official downswing phases. All of the indicators seem to identify these phases correctly, in some cases well in advance of the official turning points. The leading indicator and the BCIs exhibit troughs before the 7 official trough dates, with lead times of between 0 and 4 quarters. The coincident indicator exhibits troughs that coincide with or lag the official trough dates by 1 quarter. The leading indicator and the BCIs exhibit peaks before the official peak dates, with lead times of between 0 and 11 quarters. The cycles identified with the coincident indicator, range between a lead time of 5 quarters and a lag of 3 quarters.

Despite their favourable properties, the indicators are quite volatile and the default censoring rule produces a number of short phases (2 quarters), especially during the ambiguous period (2001-2004) and latter part of the sample period (2012-2015). The false positives are problematic for the use of the indicators as early warning signals.

The leading indicator and the BCIs provide advanced warning of turning points, albeit in some cases well before the official peaks. In this sense they are leading indicators of the business cycle turning points. The coincident indicator has a relatively stable relationship with the official cycle, although in many cases it lags the official cycle.

The co-movement between these different cycle phases can be measured with the concordance statistic suggested by Harding & Pagan (2002). The concordance statistic measures the co-movement of two series, by considering the proportion of time the two series are in the same phase simultaneously. Statistically, this entails testing whether $I = \Pr(S_{xt} = S_{yt})$ is close to 1, where $S_{xt} = 1$ identifies an expansion in financial series $\{x_t\}$, and $S_{yt} = 1$ identifies a business cycle upswing at time $t$.

Table 2 reports the concordance statistics for the phases of the indicator variables, compared to the official SARB reference turning points. The significance levels are determined with heteroskedasticity and autocorrelation consistent standard errors. All of the indicators exhibit significant concordance with the official SARB cycle. For the coincident indicator, the maximum concordance statistic occurred with a lag of 1 quarter (i.e. 1 quarter after the official cycle). For the leading indicator and the BER BCI, the maximum concordance statistics occurred with a lead of 2 quarters before the official cycle. For the SACCI, it occurred with a lead of 3 quarters.

The results imply that the BCIs, and the BER BCI in particular, are potentially useful leading indicators: they appear to follow the official SARB cycle almost as closely as the official indicators and provide similar advanced warning of turning points as the leading indicator.

**Table 2. Concordance statistics with the official SARB cycle**

| | Coincident | Leading | BER BCI | SACCI BCI |
|---|---|---|---|---|
| Lead=3 | 0.665** | 0.79*** | 0.695*** | 0.74*** |
| Lead=2 | 0.731*** | 0.808*** | 0.737*** | 0.71*** |
| Lead=1 | 0.808*** | 0.778*** | 0.719*** | 0.68** |
| Lag/Lead=0 | 0.886*** | 0.725*** | 0.689*** | 0.65* |
| Lag=1 | 0.904*** | 0.659*** | 0.635** | 0.377 |
| Lag=2 | 0.862*** | 0.593 | 0.569 | 0.365 |

*Note: *p<0.1; **p<0.05; ***p<0.01*

### *4.2.3 Predictive power for GDP growth*

In addition to leading indicator properties, the BCIs may be useful in forecasting real economic activity. Granger-causality tests can help to determine whether one time series is useful in forecasting another, by measuring the ability of lagged values of a time series to predict the future values of another time series. Table 3 reports the results for Granger causality tests for the growth rates in the indicators and real GDP growth. The results suggest that the lagged values of the coincident and leading indicators, as well as the BER BCI, significantly predict real GDP growth. In other words, the results suggest that these indicators contain relevant predictive information for output growth.

**Table 3. Granger causality tests for RGDP Growth and other cyclical indicators**

| Granger causality H0: | Statistic |
|---|---:|
| Coincident_Growth does not Granger-cause RGDP_Growth | 2.315** |
| RGDP_Growth does not Granger-cause Coincident_Growth | 1.02 |
| Leading_Growth does not Granger-cause RGDP_Growth | 2.581** |
| RGDP_Growth does not Granger-cause Leading_Growth | 1.076 |
| BER_BCI does not Granger-cause RGDP_Growth | 2.823*** |
| RGDP_Growth does not Granger-cause BER_BCI | 1.154 |
| SACCI_Growth does not Granger-cause RGDP_Growth | 1.474 |
| RGDP_Growth does not Granger-cause SACCI_Growth | 1.106 |

*Note: *p<0.1; **p<0.05; ***p<0.01*

Standard recursive vector autoregressive models (VARs) can be used to trace out the dynamic responses of economic activity to surprise increases in business confidence (Taylor & McNabb (2007), Barsky & Sims (2012)). The aim is to investigate whether the BCIs have a significant dynamic relationship with real output, and whether they contain predictive information for GDP growth.

The VAR for the BER BCI is estimated on the quarterly data running from 1973Q1 to 2016Q3, while the VAR for the SACCI BCI is estimated on the quarterly data from 1991Q4 to 2016Q3. The BER BCI enters in levels, while the SACCI BCI and real GDP series enter as annual quarter-on-quarter growth rates (unit root tests confirm the stationarity of these series). The appropriate number of lags are selected by means of the Akaike information criterion (AIC), which points to 9 lags, and a constant term is included.

The BCIs are ordered first in a recursive identification strategy, with the Cholesky decomposition used to identify structural shocks. With this ordering, shocks to confidence are allowed to have a contemporaneous impact on activity, but shocks to activity have no contemporaneous impact on confidence. This is the identification strategy and ordering used in the literature (Leduc & Sill (2013), Bachmann et al. (2013)). It can be motivated by the timing of the BER's quarterly surveys: when the survey is completed, respondents do not know the realisations of output growth, as the response deadline is generally the second month of the quarter. The results are similar for alternative orderings.

The above identification strategy allows for the generation of impulse response functions (IRFs), which can show the dynamic impact of a shock to confidence on the system. The shock itself is an innovation to the residual in the equation of the variable of interest.

Figure 4 illustrates the IRFs of the bivariate VAR using the BER BCI. The left panel plots the responses of real GDP growth to an orthogonal shock in the BER BCI, with a 95% bootstrap confidence interval (CI). Following a positive shock to confidence, real GDP growth increases by around 0.8% on impact, with a peak at three quarters. The impact on the growth rate is transitory, dying out after approximately seven quarters.

Figure 5 illustrates the IRFs of the bivariate VAR using the SACCI BCI growth. The left panel plots the responses of real GDP growth to an orthogonal shock in the SACCI BCI, with a 95% bootstrap confidence interval (CI). Following a positive shock to confidence, the increase in real GDP growth is significant only after three quarters, and smaller than is the case for the BER BCI.

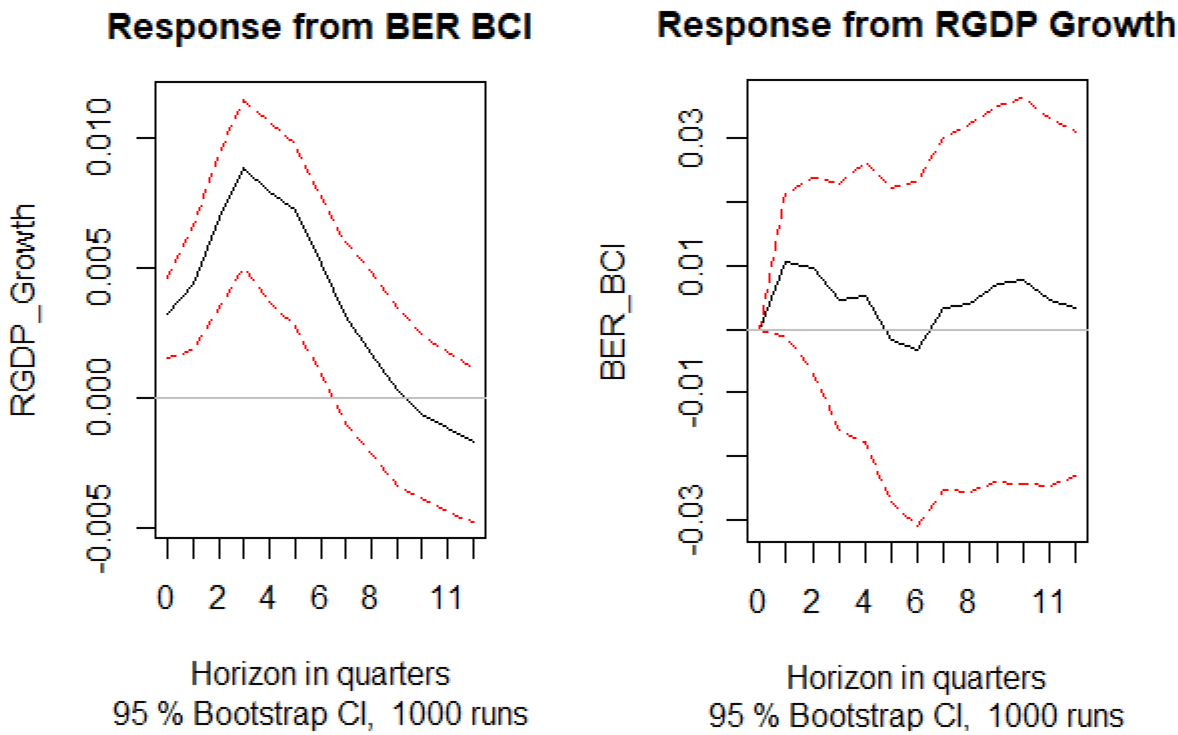



**Figure 4. IRFs of BER BCI and real GDP growth in bivariate VAR**

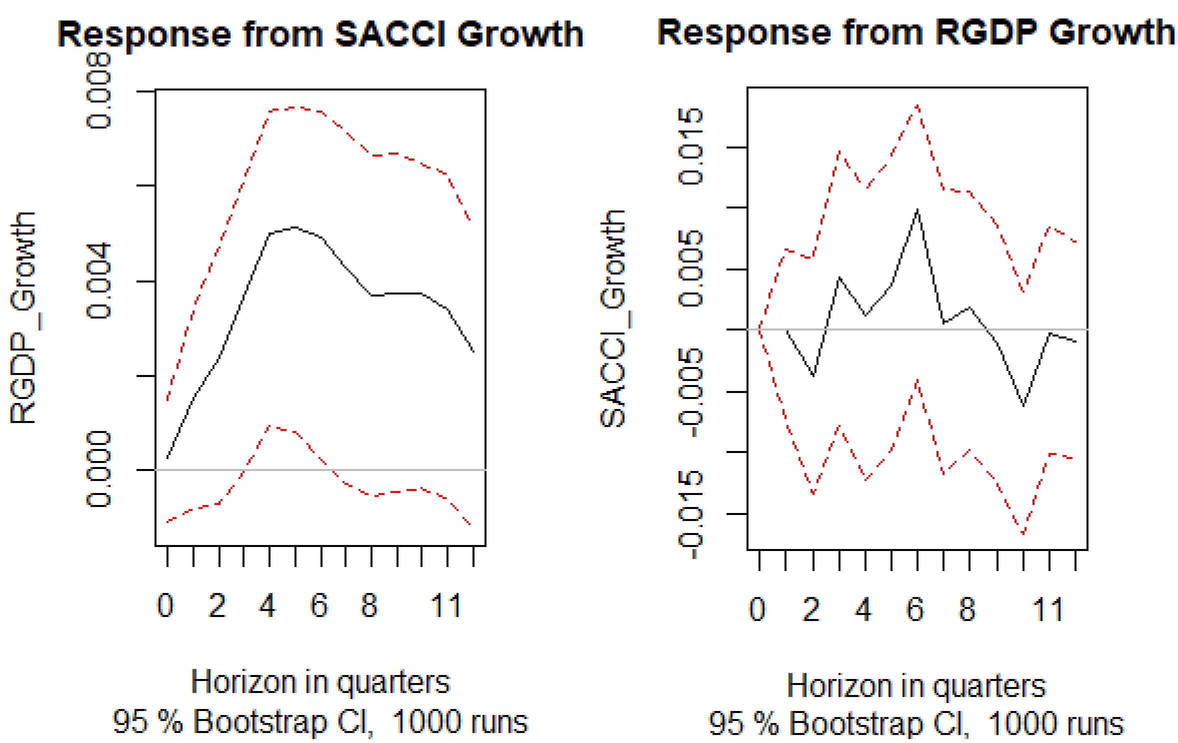



**Figure 5. IRFs of SACCI BCI growth and real GDP growth in bivariate VAR**

The system dynamics can also be examined with forecast error variance decompositions (FEVD). The FEVD shows the proportion of movements in a sequence due to its own shocks and shocks to the other variable. Figure 6 illustrates the FEVDs for the BER BCI and real GDP growth. The right panel shows that up to around half (52%) of the movements in real GDP growth are explained by the BER BCI over the longer term, while the left panel shows that real GDP explains very little of the variance in the BER BCI.

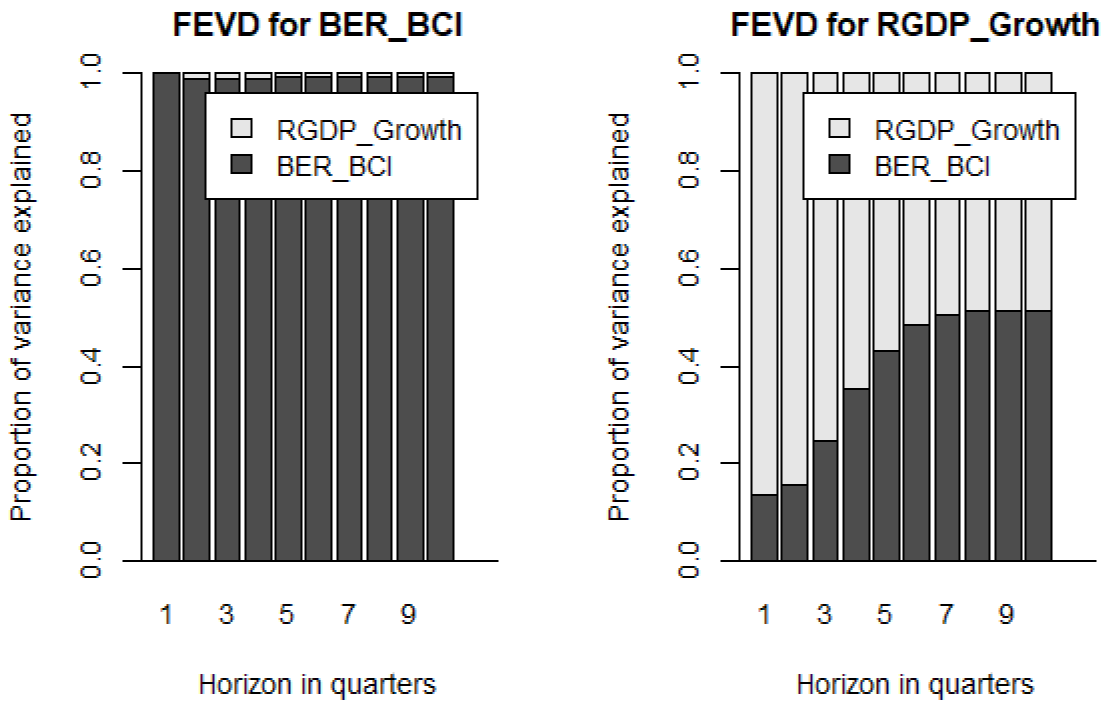



**Figure 6. FEVDs of BER BCI and real GDP growth in bivariate VAR**

Figure 7 illustrates the FEVDs for the SACCI BCI and real GDP growth. The right panel shows that up to around 35% of the movements in real GDP growth are explained by the SACCI BCI over the longer term. In terms of predictive content, the BER BCI seems to outperform the SACCI BCI.[2]

[2] The results for the coincident and leading indicators are similar to those of the BER BCI and also outperform the SACCI in terms of predictive content. The results are available upon request.

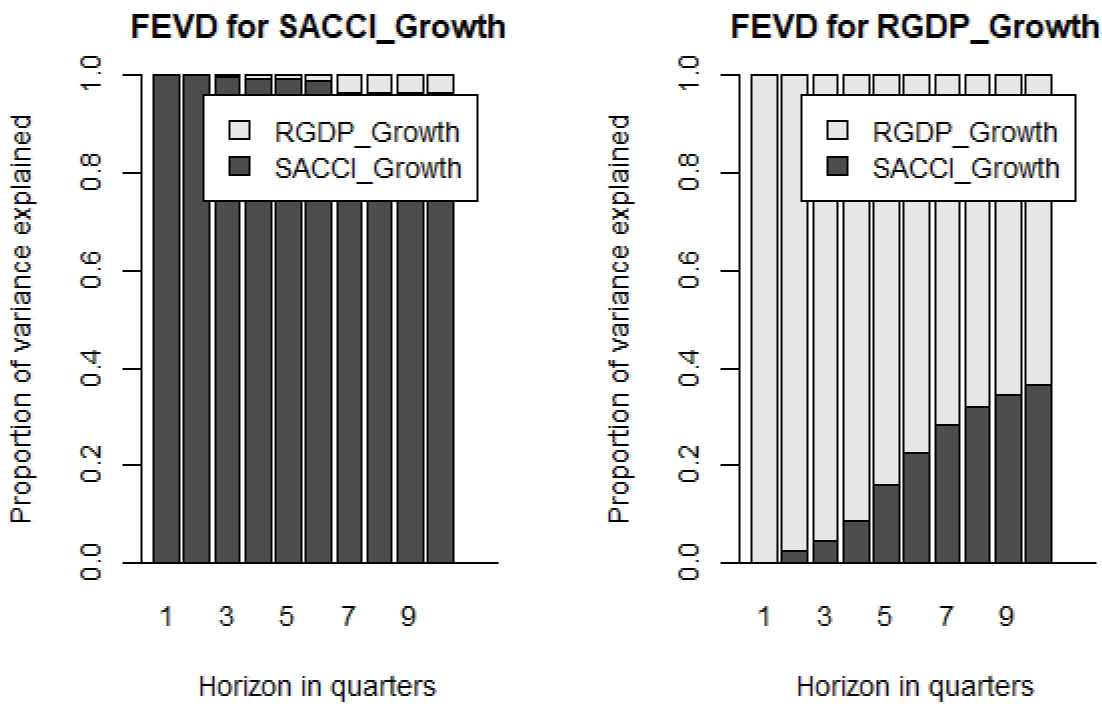



**Figure 7. FEVDs of SACCI BCI growth and real GDP growth in bivariate VAR**

A larger VAR system allows for robustness tests. We fit extended VARs including variables commonly used in the South African literature (Leduc & Sill (2013) and Redl (2015)): the BER or SACCI BCI, the Johannesburg Stock Exchange All Share Index (JSE), the yield spread (i.e. the Government Bond Yield minus the 3-month T-Bill rate), real GDP, industrial production, investment, and an employment index. The variables are ordered with the confidence indicators first, the financial variables next and the real variables last. As was the case for the previous VAR, the variables enter as real annual quarter-on-quarter growth rates, except for the BER BCI and the yield spread. The VARs are estimated on the quarterly data running from 1992Q1 to 2016Q3 and include 4 lags.

Figure 8 illustrates the impact of the BER BCI on the growth in real GDP, real industrial production and real investment. The larger system yields similar results to those of the bivariate VARs earlier. The impact of the shocks are larger on real production and investment growth than on real GDP growth. Figure 9 illustrates the impact of the SACCI BCI on the growth in real GDP, real industrial production and real investment. The results are similar to the larger system using the BER BCI, although impacts are slightly smaller.

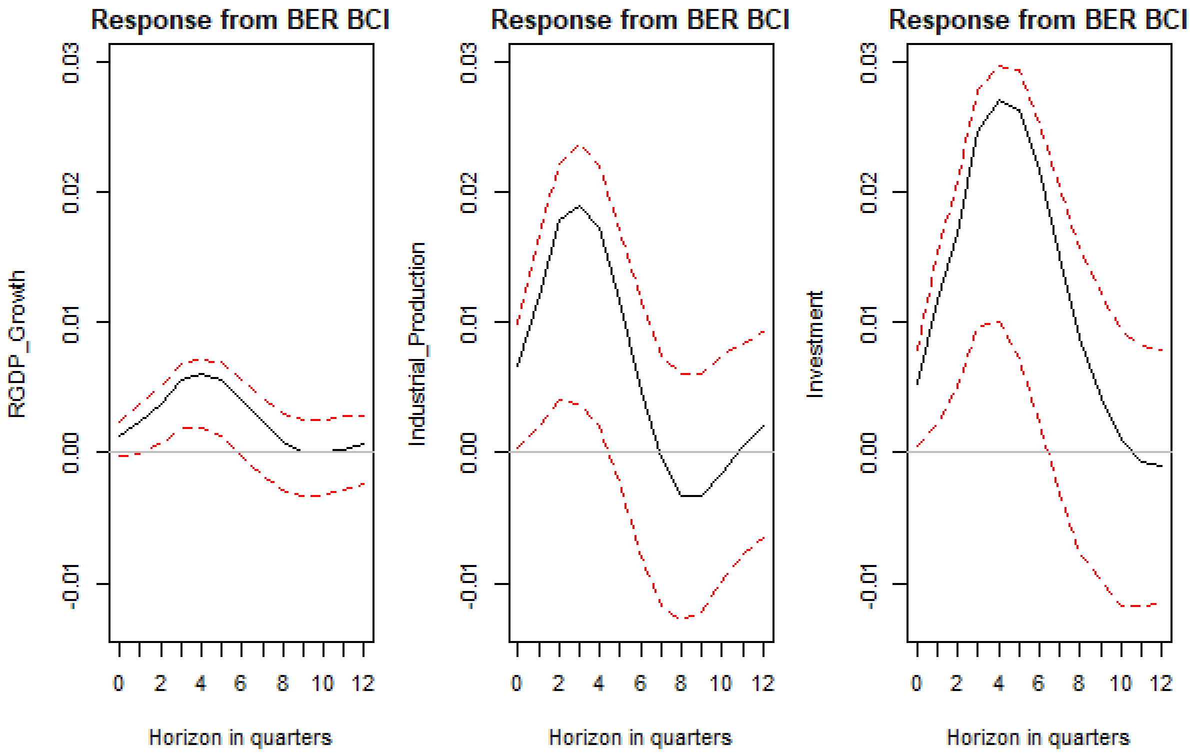



**Figure 8. IRFs of BER BCI on real GDP, industrial production and investment growth in extended VAR**

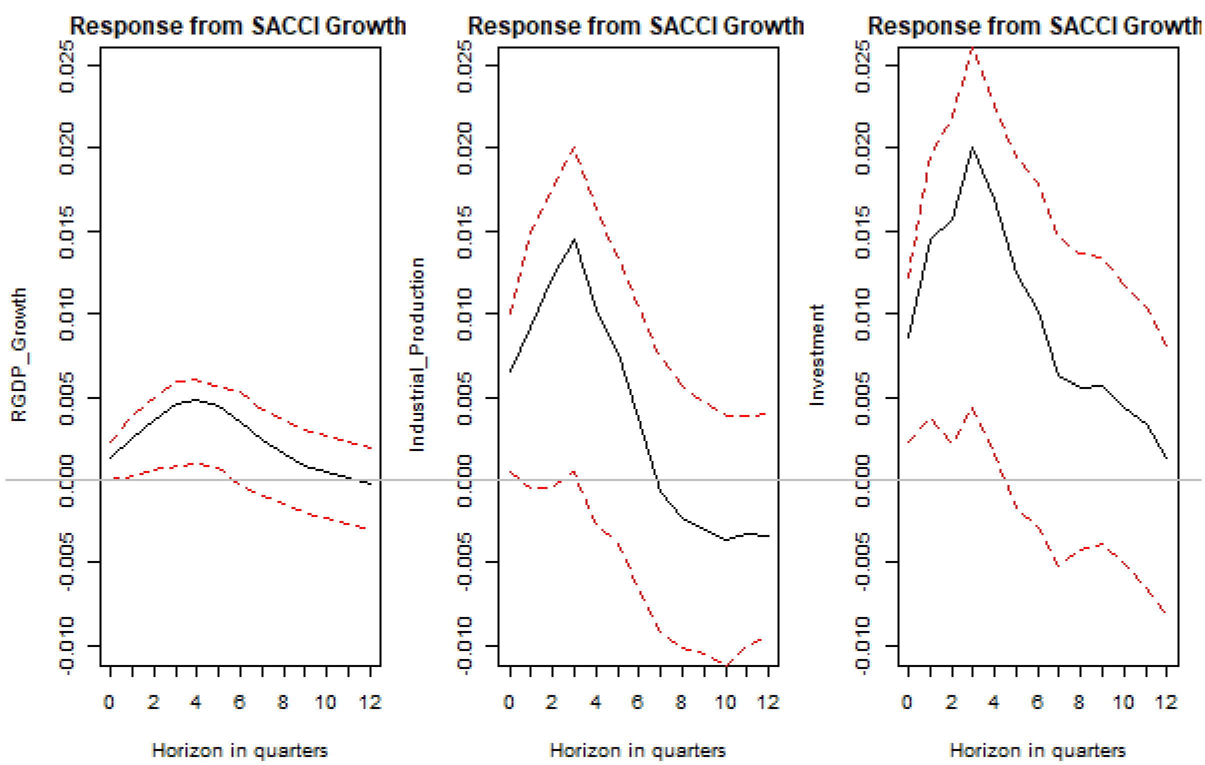



**Figure 9. IRFs of SACCI growth on real GDP, industrial production and investment growth in extended VAR**

According to the FEVD illustrated in Figure 10, the BER BCI explains around 35% of the variance in real GDP growth. The numbers are similar for real production growth and real investment growth. The BER BCI therefore seems to contain useful predictive information for real activity growth. According to the FEVD illustrated in Figure 11, the SACCI BCI explains around 30% of the variance in real GDP growth. The numbers are similar for real production growth and real investment growth.

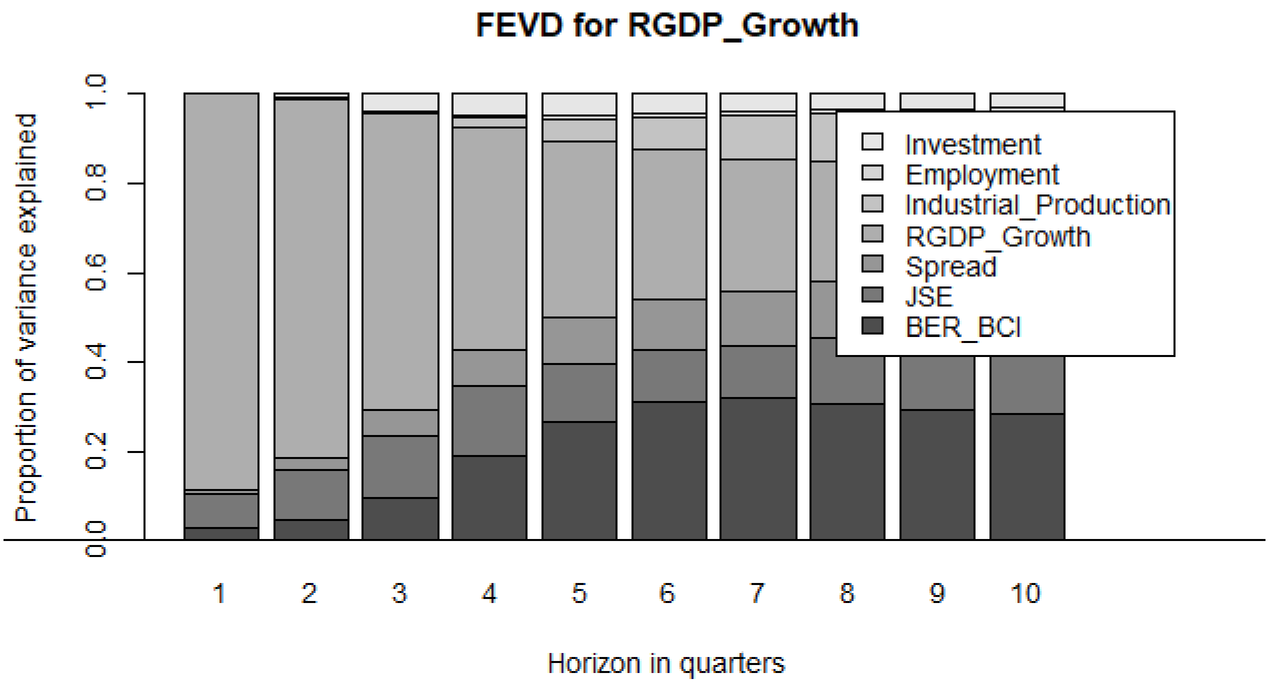



**Figure 10. FEVDs real GDP growth in the extended VAR with the BER BCI**

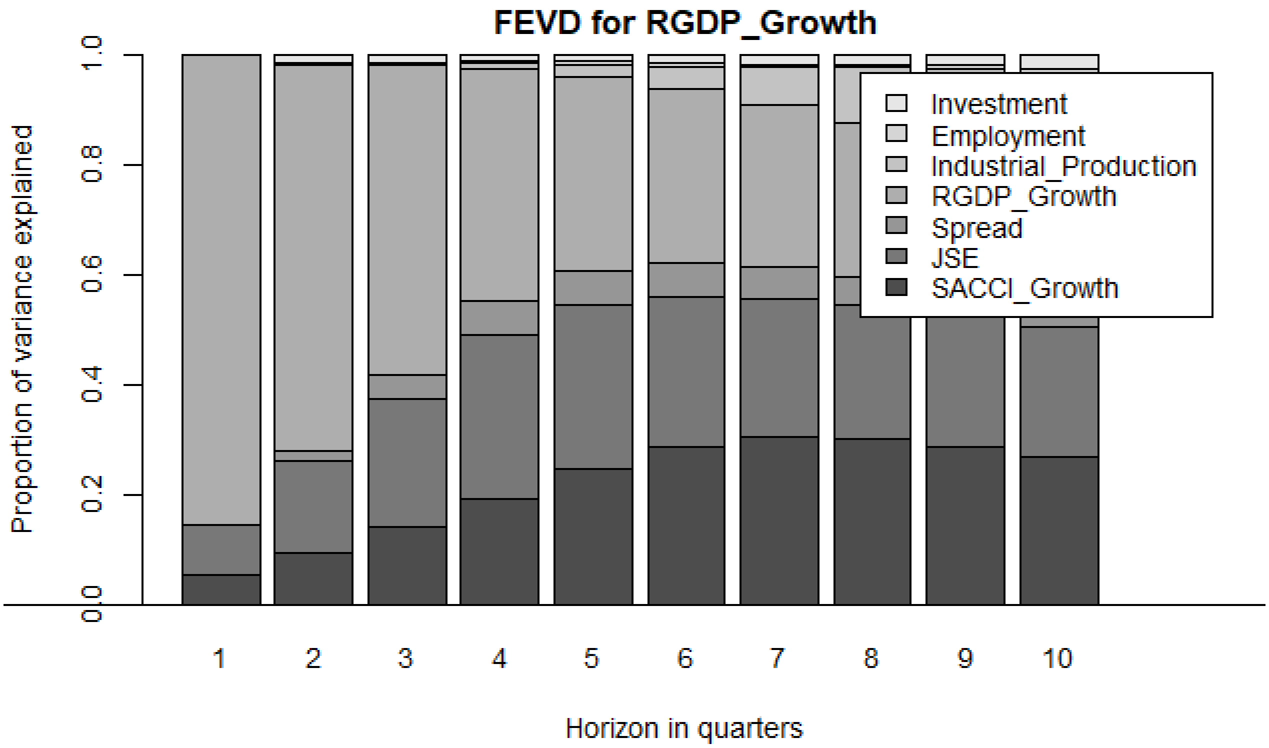



**Figure 11. FEVDs of real GDP growth in the extended VAR with the SACCI BCI**

Our empirical analysis suggests that the BCIs, and the BER's BCI in particular, are useful leading indicators of the business cycle and track the official business cycle relatively closely. The business confidence indicators perform similar to the SARB's official coincident indicator in predicting turning points. The BCIs also contain relevant information for the prediction of output growth.

## 5 An Alternative Algorithm for Dating South Africa Business Cycle Recessions

Given the performance of the BER's BCI as indicator of the South African cycle, further research at the BER has explored the extent to which an alternative multi-variable approach can accurately predict cyclical turning points. In particular, the aim was to identify an approach reliant on a smaller set of economic variables than the large set currently considered by the SARB.

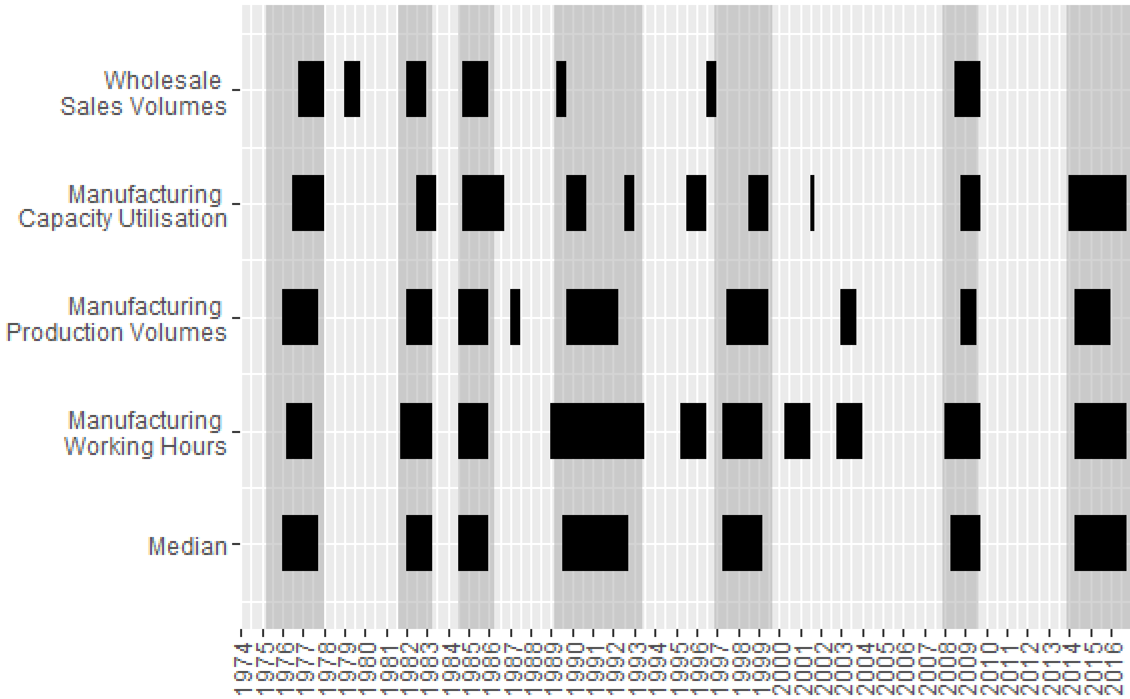
Laubscher (2014) identifies five time series that are close predictors of the official reference business cycle turning points identified: the BER BCI; manufacturing volume of production; manufacturing capacity utilisation; manufacturing working hours and wholesale sales volumes. Laubscher then combines these five time series with information from the yield curve to develop a two-stage algorithm for predicting cyclical turning points.

In the first stage, the algorithm relies on advance signals from the yield spread (between 10-year and 3-month government bonds). The algorithm identifies a possible business cycle peak when the 6-month advanced probability of recession, calculated from the yield spread, exceeds the 50% threshold.

In the second stage, the algorithm involves an evaluation of the five time series listed above. A probable recession is identified on the basis of pre-defined thresholds for each of the series. Thereafter, it is determined whether the latest reading of each of the series signal a peak (or trough), i.e. when the second derivative is maximally negative (or positive). Censoring rules are applied to take care of spurious fluctuations in specific time series. In line with Boshoff (2005), full cycles with a duration shorter than 15 months and phases shorter than 6 months are eliminated. The candidate turning point is also required to adhere to a generality requirement, by clustering with turning points in three or four other series, in order to be classified as a turning point. The candidate turning point dates suggested by the indicators are reconciled by relying on the median turning point date across the five series.

Laubscher's (2014) *ex post* evaluation indicates that the algorithm is successful at dating the five recessions between 1981 and 2013. While the data tends to be volatile, all spurious signals can be discarded on the basis of the censoring rules or of the generality requirement. For the best fit, Laubscher (2014) suggests that the manufacturing capacity utilisation indicator only be used for trough signals, and that the wholesale sales index only be used to confirm a business cycle turning point suggested by the other indicators. The proposed algorithm achieves a high degree of accuracy, with a median two-month lag at business cycle peaks and a one-month lead at troughs. Laubscher (2014) converted the quarterly BER BCI to a monthly frequency, by assuming the same quarterly value for each month of the quarter, and calculating a five-month moving average. The evidence suggests that the algorithm would not only allow 'close calls' on turning points, but would also be able to do this with a much shorter time delay than the SARB's official decisions. The median announcement lag was eight months and five months for peak and trough signals respectively, implying an average lead of 10 months and 19 months over SARB decisions.

We update the ex-post evaluation to investigate the performance of the algorithm in predicting the most recent downswing phase in South Africa, dated as starting in November 2013. Figure 12 shows updated data elucidating the relationship between official business cycle turning points and turning points in four of the five series used by the Laubscher algorithm. The fifth series, the BER BCI, was analysed in the preceding section. The grey columns indicate the official SARB downswing phases, while the black rectangles show the downswing periods for each series. The individual series performed relatively well in predicting the most recent downswing phase, although all four of the series lagged the official cycle by a few months, and wholesale sales volumes did not indicate a peak.




*Notes: Black rectangles indicate the downswing periods identified for each series. Grey columns indicate the official SARB downswing phases.*

*Source: Laubscher (2014), updated by Pieter Laubscher*

**Figure 12. Recessionary periods in the four indicators and the median (official SARB downswing phases shaded)**

Figure 12 also illustrates the median turning point dates, using the algorithm described above: the median of three dates for peaks (i.e. business confidence, manufacturing production and manufacturing hours) and four dates for troughs (i.e. the aforementioned three and manufacturing capacity utilization). The results indicate that the recession dating algorithm is relatively accurate, even in identifying the most recent growth cycle downswing phase. As there was no turning point in wholesale sales volumes, the algorithm recommends that more information should be analysed in order to confirm the turning point. Overall, the recession dating algorithm illustrates the value of combining different leading indicators and allows a decision to be made with a shorter delay than the SARB's official determination.

## 6 Conclusion

This paper has discussed the role of indicators of the official South African business cycle developed by research institutes outside of the South African Reserve Bank. The SARB identifies turning points with reference to leading, coincident and lagging indicators, as well as comprehensive historical and current diffusion indices. These indicators have tracked the official business cycle turning points reasonably well. Even so, there is a significant delay in both the publication of the SARB indicators and the determination of the official turning point dates and these indicators are subject to revision.

As alternative indicators, we consider two business confidence indicators published in South Africa, one by the BER and one by SACCI. The two business confidence indicators, and the BER BCI in particular, are useful leading indicators: their classical business cycles track the official South African growth cycle relatively closely. They provide advanced warning of turning points, although there were a few false signals, especially over the ambiguous period of 2000-2003. Their performance is on par with the performance of the SARB's official indicators in cyclical prediction. Even so, these business confidence indicators have the important benefit that they are published before the other series become available and are not subject to revision. The BCIs also contain relevant information for the prediction of output growth. Shocks to the BCIs accounted for a sizeable fraction of variation in economic activity in our rudimentary VAR analysis. As a result, these business confidence indicators are useful for monitoring economic developments in a timely manner and for forecasting future economic activity.

Further business cycle research at the BER suggests that an alternative recession-prediction algorithm relying on classical cycles in six variables, including the yield curve, the BER's BCI and various manufacturing-related variables, are successful at predicting official growth cycle peaks and troughs in South Africa. This algorithm allows the dating of turning points with a shorter time delay than the SARB's official decisions.

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