

# BUSINESS CONFIDENCE AND THE BUSINESS CYCLE IN SOUTH AFRICA

Laurie H. Binge<sup>1</sup>, Willem H. Boshoff<sup>2</sup>  
*Stellenbosch University, Stellenbosch, South Africa.*

November 8, 2017

Business confidence indicators are widely used leading indicators of economic activity. It is therefore important to measure them as accurately as possible. This chapter constructs improved composite indicators of business confidence for South Africa, based on the microdata from the BER's business tendency surveys. Moreover, the potential role of low confidence and heightened uncertainty in shaping the Great Recession and the lacklustre subsequent recovery has motivated a large body of international literature investigating the impact of changes in business sentiment on real economic activity. The new confidence indicators are used to examine whether there is a significant positive relationship between confidence and real GDP growth, the timing of this relationship, and whether it remains significant after taking other economic variables into account. The composite confidence indicators improve on existing indicators in that they exhibit higher correlation with real GDP growth and higher concordance with the official SARB business cycle. The new indicators seem to contain useful information about current and future economic developments.

**JEL Classification:** C83, D81, E32

**Keywords:** Business Tendency Surveys, Confidence, Business Cycle Indicators

## 1 Introduction

Business confidence indicators, such as the European Commission's Economic Sentiment Index, are popular and useful leading indicators of economic activity in many countries (United Nations, 2015). This is also the case in South Africa, where the Bureau for Economic Research's Business Confidence Index (BER BCI) is often quoted and is used by the SARB as a leading indicator to identify the official business cycle turning points (Bosch, 2015). Given that business confidence indicators are popular and potentially useful, it is important to measure them as accurately as possible.

Only two business confidence indicators are regularly published for South Africa: the BER BCI and the South African Chamber of Commerce and Industry Business Confidence Index (SACCI BCI). However, both have some shortcomings. The SACCI BCI is a composite measure of economic activity, rather than a confidence indicator in the way used in the literature. The BER BCI is a measure of confidence derived from the BER's business tendency surveys. It is based on a single question, weighted in an ad hoc manner, and excludes the services sector altogether.

This chapter estimates new proxies for business confidence using micro-data from the BER business tendency surveys, with the aim of improving on the existing measures for South Africa. Although measuring business confidence is challenging, survey-based indicators can be helpful in discovering key economic agents' opinions on future economic developments (Girardi and Ruiter, 2015). Survey-based confidence indicators have the advantage that they are published long before the official statistics become available and are not subject to revision (European Central Bank, 2013).

The idea that weak business confidence and heightened uncertainty contributed to a large extent to the Great Recession and to the lacklustre subsequent recovery has inspired a substantial international

---

<sup>1</sup>PhD candidate at the Department of Economics at Stellenbosch University. Corresponding author email address: [lhbinge@gmail.com](mailto:lhbinge@gmail.com)

<sup>2</sup>Associate Professor at the Department of Economics at Stellenbosch University. Email address: [wimpie2@sun.ac.za](mailto:wimpie2@sun.ac.za)

literature examining the impact of changes in sentiment on output and investment decisions. Yet, to date there has been little research on business confidence in South Africa (e.g. Pellissier (2002)), in part due to the difficulty of measurement.

This chapter investigates the relationship between the survey-based business confidence indicators and real economic activity in South Africa. The aim is to study whether there is a significant positive relationship between the indicators and real GDP growth, the timing of this relationship, and whether it remains significant after taking other economic variables into account.

## 2 Confidence

Business confidence involves firms' perceptions of, or degree of optimism regarding, current business conditions and the expected future business climate (Mendicino and Punzi, 2013). In this chapter, firms' perceptions of current and future business conditions are measured using the BER business tendency surveys. Two sets of composite confidence indicators are calculated, as the weighted cross-sectional mean of responses to questions on current and expected future business conditions (Organisation for Economic Co-operation and Development, 2003).

This section provides a brief review of the literature on confidence. It begins with a review of the theoretical links between confidence and macroeconomic outcomes. The empirical literature is then discussed, focusing on the approaches to operationalising the definition of confidence, and the evidence on the impact of confidence on economic outcomes.

### 2.1 Macro Theory and Confidence

Although confidence measures are popular leading indicators of economic activity in many countries, a review of the academic literature suggests three alternative views. These range from the view that confidence measures have an important causal role in the business cycle, to the view that they contain useful predictive information but play a limited causal role, to the view that they have no value, even in forecasting (Barsky and Sims, 2012).

According to the so-called 'animal spirits' view, psychological factors have a causal impact on economic fluctuations distinct from fundamentals (Carroll, Fuhrer and Wilcox, 1994). This view is most closely associated with Keynes (1936), who argued that: "Our decisions to do something positive, the full consequence of which will be drawn out over many days to come, can only be taken as a result of animal spirits - of a spontaneous urge to action rather than inaction, and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities." The original Keynesian view finds resonance in the more recent literature, with Akerlof and Shiller (2015) arguing that in the face of uncertainty, decisions about the future are based on animal spirits, rather than a weighted average of quantitative benefits and probabilities, as rational theory would dictate. According to the animal spirits view, therefore, confidence has a potentially important causal impact on economic outcomes.

In contrast, the so-called 'news' view argues that confidence indicators contain useful predictive information for economic output, but play a limited causal role. According to the news view, any relationship between confidence measures and subsequent real activity means that confidence measures contain information about current and future fundamentals of the economy (Barsky and Sims, 2012). Confidence can proxy for news that agents receive about future productivity,

which is not yet reflected in econometricians' information sets, by aggregating information from various sources (Cochrane, 1994; Barsky and Sims, 2012). Confidence indicators reflect agents' expectations about future fundamentals and economic conditions, which are not summarised in other macroeconomic variables. When agents are optimistic, they give positive responses to surveys. These are confirmed, on average, and real activity eventually increases as predicted by the confidence indicator (Carroll, Fuhrer and Wilcox, 1994).

From the rational expectations point of view, confidence should reflect the expected values of economic fundamentals and should not offer any additional predictive information (Beaudry and Portier, 2004). However, a number of studies (e.g. Beaudry and Portier (2004) and Van Aarle and Kappler (2012)) analyse models where agents receive imperfect signals about future productivity growth and use these signals to make investment decisions. In this context, confidence refers to a state where agents receive an above-average signal, which may generate a wave of optimism. Rational agents then learn gradually about the true state of the economy and adjust their expectations. Other factors, such as frictions in capital markets, may also explain predictive information contained in confidence indicators (European Central Bank, 2013).

The literature therefore sets out theoretical links between confidence and economic activity. Yet, it is not clear whether confidence indicators repackage information already contained in other economic variables, or whether they contain useful independent predictive information about the economy. If they contain predictive information, it is not clear whether they reflect animal spirits, or aggregated information on agents' expectations of future outcomes not captured by the macroeconomic data (Mendicino and Punzi, 2013; Akerlof and Shiller, 2015).

## **2.2 Empirical Findings**

Although the findings in the empirical literature have not been conclusive, the majority of studies seems to find that confidence indicators are at least positively related to real economic activity (Taylor and McNabb, 2007). The inconclusive findings may be due to two main challenges: constructing proxies for confidence and establishing whether it has a separate causal impact on real economic activity.

### **2.2.1 Measuring Confidence**

Confidence cannot be observed or measured directly, which makes it challenging to construct confidence measures (Santero and Westerlund, 1996). Analysts typically aggregate responses from business and consumer surveys. These surveys usually contain a small number of qualitative questions, which can be answered quickly by respondents. Indicators are derived from the subjective answers to questions on past, current and future developments. The assumption is that agents' form opinions about economic conditions before a specific business activity is implemented (e.g. new production plans, employment, or purchases). These opinions may be called 'confidence'.

The most common and widely used method to aggregate survey responses is to calculate balance statistics. In the context of business tendency surveys, balances are averages of survey responses. For most survey questions, there are three reply options, e.g. 'up', 'the same', or 'down'. Balances are calculated as the difference between the percentage of positive answers and negative answers. Balances are simple to calculate and understand, and are considered both practical and entirely adequate for cyclical analysis (Organisation for Economic Co-operation and Development, 2003).

Although balances are by far the most common method used by statistical agencies and analysts to aggregate the surveys, a few more sophisticated methods have been discussed in the literature, including a probabilistic approach, a regression approach, and a latent factor approach (Nardo, 2003). However, these approaches usually require actual quantitative reference series for the relevant variables, which is restrictive in the case of business confidence. Moreover, these methods can become unreliable when exceptional events have a large impact on the correlation between the survey data and the quantitative reference data (United Nations, 2015). Nevertheless, the evidence suggests that balance statistics tend to produce indicators that are very similar to those produced by more sophisticated methods (Organisation for Economic Co-operation and Development, 2003; Driver and Urga, 2004). Weighted balance statistics are therefore used in this chapter to calculate summary statistics of the responses to each survey question.

The balances from multiple questions are typically used to calculate composite confidence indicators, as opposed to using a single question. As no single cause explains all cyclical fluctuations over the long term, it is necessary to have information from many possible sources of change, i.e. to use all potentially important information (Van Aarle and Kappler, 2012). Composite indicators have the capacity to react to various sources of economic fluctuations, while being resilient to fluctuations affecting single components. They often have fewer false alarms and fewer missed turning points than individual components and tend to have more stable lead-times. (European Central Bank, 2013). In this chapter, composite confidence indicators are calculated by incorporating the responses to a number of questions.

Composite confidence indicators of this type are available for most countries. The European Commission, for instance, builds composite indicators by aggregating the survey responses from five sectors, using multiple questions on current and expected conditions (Organisation for Economic Co-operation and Development, 2003). The aggregate Economic Sentiment Index is a weighted average of confidence in the manufacturing, construction, retail, and services sectors, as well as for consumers (European Central Bank, 2013). Another prominent example is the Ifo Business Climate Indicator, which is used as a leading indicator in Germany (United Nations, 2015).

Two indicators of confidence are published in South Africa: the BER BCI and the SACCI BCI. The SACCI BCI is a composite index of 13 quantitative sub-indices thought to have the greatest influence on the business mood. 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. The SACCI BCI is an *ex post* measure of actual activity, which is dependent on external macroeconomic variables. The rationale is that recent business activity is indicative of the degree of business confidence (SACCI, 2011). In this sense, the SACCI BCI is a composite measure of economic activity, rather than a confidence indicator in the way it is used in the literature.

The BER BCI is constructed from the BER's quarterly business tendency surveys, which are similar to the business tendency surveys conducted all over the world. The BER BCI has proved useful as a leading indicator of the business cycle and economic growth in South Africa. It is used as one of twelve leading indicator series by the SARB to date official turning points in the business cycle. Laubscher (2014) also found that it can improve advanced estimates of cyclical turning points. This is particularly useful in view of the early availability of the index. The BER index results for a particular quarter are available approximately two months before the official GDP estimates (Kershoff, 2000).

In calculating the business confidence indicator, the most important issues are which survey questions

to use and the weights applied to the responses. The BER BCI is constructed from a specific question (Q1) that appears in all of the surveys: “Are prevailing business conditions: satisfactory, or unsatisfactory?” The BCI is the weighted percentage of respondents who rated prevailing business conditions as ‘satisfactory’ and is therefore based on the perceptions of business people (Kershoff, 2002). According to Kershoff (2000) there are two reasons for the use of this one question to construct the confidence indicator. Firstly, it is reasonable to assume that respondents who are satisfied with business conditions will have more confidence than those experiencing unsatisfactory conditions. Secondly, respondents take a variety of factors into account when rating prevailing business conditions, which solves the problem of weighting different factors (Kershoff, 2000).

In line with international best practice, all survey responses are weighted (except for the building survey). Each response is multiplied by a factor, which is calculated as the product of a firm size weight and a subsector size weight (except for the motor trade, where there are no subsectors). Each firm receives a weighting in relation to turnover, or the size of workforce in the case of manufacturing. The subsector size weights are based on the composition of production or sales in each subsector, as calculated by StatsSA. Balances are calculated to obtain five sectoral indices: manufacturing, building contractors (other construction subsectors are omitted), retailers, wholesalers and new vehicle dealers. The BER BCI is calculated as the unweighted mean of the five sectoral indices (services are excluded altogether).

The BER BCI is therefore a measure of current conditions, based on a single question, with survey responses weighted in an ad hoc manner. The business surveys contain a number of questions, all of which potentially have an impact on business confidence. A composite indicator can be calculated by combining the responses to a number of questions, which is often done internationally (European Central Bank, 2013). Moreover, the BER BCI reflects confidence in current conditions. As the surveys contain questions on expectations, forward-looking responses may also provide valuable information.

This chapter aims to build on the BER BCI, by using the BER business tendency survey micro-data to calculate new composite weighted indicators of confidence. The composite indicators incorporate the survey responses to a number of questions, maintaining a distinction between current and expected conditions. The responses are weighted to produce sectoral and aggregate indicators. These confidence indicators are then used to investigate the relationship between confidence and economic activity. The following section provides a review of the evidence on the impact of confidence on economic outcomes.

## **2.2.2 The Impact of Confidence**

The majority of studies seems to find that confidence indicators are at least positively related to real economic activity, although this does not necessarily imply a causal relationship (European Central Bank, 2013). Confidence indicators have been found to be useful in some cases as leading indicators, as well as for forecasting, even after controlling for other economic variables. Even in cases where the unique information content is limited, the timeliness of survey indicators may make them useful for monitoring developments and for real-time forecasting (nowcasting).

The empirical literature has often investigated the extent to which confidence indicators contain predictive information over and above economic fundamentals (United Nations, 2015). A number of studies have shown that both consumer and business confidence indicators provided valuable information for forecasting real activity, which was not contained in other economic variables (e.g.

Santero and Westerlund, 1996; Ludvigson, 2004; Kabundi, 2004; Parigi and Golinelli, 2004; Taylor and McNabb, 2007; Leduc and Sill, 2013; Mendicino and Punzi, 2013; and Kilic and Cankaya, 2016). In an influential study, Barsky and Sims (2012) found that positive shocks to consumer confidence led to significant, slow-building, and permanent responses in consumption and income. If confidence contained no news about future fundamentals, and reflected only ‘animal spirits’, one would expect transitory responses. Barsky and Sims (2012) concluded that their results supported the ‘news’ view of confidence.

The European Central Bank (2013) found that confidence indicators can play a significant role in predicting recessions. They included the European Consumer Sentiment Index, along with the OECD leading indicator for the euro area in a probit model. This model captured business cycle phases relatively well, with probabilities increasing when recessions occurred. The drawback was that probabilities also increased in some periods when there were no recessions, i.e. there were some false positives.

Even in cases where confidence indicators are just a synthesis of economic variables and the unique information content is limited, the timeliness of survey indicators may make them useful for monitoring economic developments and for real-time forecasting (Gayer, Girardi and Reuter, 2014). In the euro area, for instance, official statistics are released at least 45 days after the reference month, while business surveys are usually available before the end of the reference month. The BER BCI and the SACCI BCI are published four and two weeks before the end of the reference quarter. Confidence indicators can provide valuable information on the evolution of the economy over this period, which is one of the reasons why they are popular (Parigi and Golinelli, 2004). In this sense, even if the confidence indicators are coincident indicators of real activity, that they are available earlier means that they are quasi-leading indicators.

A number of studies have demonstrated that confidence indicators are useful for nowcasting economic activity. Matheson (2007) and Gayer, Girardi and Reuter (2014) evaluated the impact of new releases of financial, real and survey data on nowcasting GDP throughout each quarter. They found that business survey indicators improved real-time forecasting accuracy. Confidence indicators contained predictive content even after controlling for timeliness, due to their broad sectoral coverage and forward-looking nature. Kabundi, Nel and Ruch (2016) included the BER Consumer Confidence Index (BER CCI) and the SACCI BCI to forecast real GDP growth in South Africa in real time. They argued that the timeliness of the variables was especially important.

Relatively few studies have analysed business confidence indicators in South Africa. Pellissier (2002) examined the ability of the two South African business confidence indicators, the BER BCI and SACCI BCI, as business cycle indicators. He argued that both BCIs seemed to exhibit a coincident rather than a leading relationship with the business cycle, and that the BER BCI seemed to display stable turning point attributes. More recently, Laubscher (2014) found that the BER BCI was one of the closest predictors of the official reference business cycle turning points and was useful as a leading indicator. The BER’s BCI is also used by the SARB as one of the component series of its official leading indicator of the business cycle (Venter, 2005).

In this chapter, an attempt is made to establish whether there is a significant positive relationship between the indicators and real GDP growth, the timing of this relationship, and whether it remains significant after taking other economic variables into account.

### 3 Data: The BER Business Tendency Surveys

The BER, a research institute attached to Stellenbosch University, has been conducting quarterly business tendency surveys in South Africa since March 1954. These surveys are similar to the business tendency surveys conducted all over the world, including the European Commission Business Tendency Surveys and the German Ifo Business Climate Survey (Organisation for Economic Co-operation and Development, 2003).

During the last month of each quarter, questionnaires are sent to 1,000 firms in each of the manufacturing and services sectors and 1,400 firms in each of the construction and trade sectors (i.e. retail, wholesale and motor vehicles). The questionnaires are completed by senior executives of the firms. The questions have remained largely unchanged since inception, and include those on current and expected future developments regarding, among others, sales, orders, inventories, prices, employment, and constraints. For the most part, the survey answers fall into three categories: ‘up’, ‘the same’ or ‘down’.

Table 1 reports the details of the survey data. The sample runs from 1992Q1 to 2016Q3, although the survey of the services sector started only in 2005Q2.<sup>3</sup> Around 1,000 completed questionnaires are received every quarter, leading to an overall sample size of 119,438. All of the surveys have a few missing quarters, when the micro-data was lost.

Table 1: Sample characteristics

Sector	Sample	Total Obs	Obs/Quarter	Response Rate	Missing Quarters
Manufacturing	1992Q1-2016Q3	36915	384.53	0.38	1997Q4,2000Q1,2005Q4
Construction	1993Q2-2016Q3	28139	312.66	0.22	1993Q4,1998Q3,2000Q2,2005Q4
Trade	1992Q2-2016Q3	40480	426.11	0.30	1992Q4,1993Q3,2005Q4
Services	2005Q2-2016Q3	13904	308.98	0.31	2005Q4
Total	1992Q1-2016Q3	119438	1218.76	0.25	2005Q4

The sample of firms remains relatively stable from one survey to the next, effectively creating a panel. The panel is partly fixed and partly rotating, as inactive firms that fail to respond for a period of two years are removed and replaced with new firms. The fixed part reflects the opinions of the same firms over time, which ensures that the results remain comparable between surveys. The results are more likely to reflect changes in the variables under consideration than changes in the sample from one survey to the next (Kershoff, 2002).

Stratified deliberate sampling is used to design the BER’s survey panels, which is the international norm. Participants are selected to be representative of particular sectors, regions and firm sizes. The respondents are reviewed periodically to ensure reasonable representation of the population universe. The exact number of firms in the universe is unknown to the BER, as censuses of the business sector are not conducted regularly and the BER does not have access to the National Business Register (Kershoff, 2002). Practical experience has shown that non-random samples can give acceptable results in conducting these types of surveys (Organisation for Economic Co-operation and Development, 2003).

The BER makes no provision for firms that were not selected or did not respond during sampling, implicitly assuming that the non-participating or non-responding firms have the same distribution as the responding firms for the period. This corresponds with the ‘missing at random’ assumption suggested by the Organisation for Economic Co-operation and Development (2003). Kershoff (2015)

<sup>3</sup>The microdata for architects, quantity surveyors and civil engineers are only available from 2001Q1.

argued that this is a reasonable assumption, given that the responses cannot vary infinitely, and the same factors influence firms in the same sector. Kershoff (2002) found that the degree of representation of the BER's construction and trade panels adequately reflects the universes, taking response rates into account and comparing the composition of the survey panels with census and other official data.

## 4 Methodology

This section provides the methodology for calculating the confidence indicators based on the micro-data from the BER business tendency surveys. Similar to the University of Michigan, two sets of composite confidence indicators are calculated: the weighted cross-sectional mean of responses to questions on current and expected future business conditions (Organisation for Economic Co-operation and Development, 2003; Ludvigson, 2004).

### 4.1 Measuring Confidence

Formally, one can define a  $k$ -period-ahead expectations measure of confidence ( $C_t^k$ ) at time  $t$  as:  $C_t^k = E_t f(\Delta^h Y_{t+k})$ , where  $Y_{t+k}$  is a measure of real activity (usually output) at time  $t+k$  and  $\Delta^h Y_{t+k} = Y_{t+k} - Y_{t+k-h}$ . A common definition of  $f(\Delta^h Y_{t+k})$  relies on an up, unchanged, or down classification (e.g. Q2A in the BER survey):

$$f(\Delta^h Y_{t+k}) = \begin{cases} -1, & \text{if } \Delta^h Y_{t+k} < 0 \\ 0, & \text{if } \Delta^h Y_{t+k} = 0 \\ 1, & \text{if } \Delta^h Y_{t+k} > 0 \end{cases}$$

An alternative would be to use a binary classification (e.g. Q1 in the BER survey):

$$f(\Delta^h Y_{t+k}) = \begin{cases} -1, & \text{if } \Delta^h Y_{t+k} < a \\ 1, & \text{if } \Delta^h Y_{t+k} \geq a \end{cases}$$

where  $a$  is determined by the preferences of the agent.

In this chapter, a distinction is made between indicators of current conditions  $C_t^k$  when  $k = 0$ , and indicators of expected conditions  $C_t^k$  when  $k = 1$ . The confidence measure for current conditions  $C_t^0$  is referred to as 'current', as it reflects confidence about the current quarter (in the second month of the quarter). The confidence measure for expected conditions  $C_t^1$  is referred to as 'expected', as it reflects confidence about the following quarter.

The BER business tendency surveys make this distinction possible by asking for separate responses relating to current and expected future conditions. The questions on current conditions (e.g. Q2A) all have the following format: "(Estimated development in current quarter) Compared with the same quarter of a year ago, are general business conditions: better, the same, or poorer?" In other words, these questions ask whether the factor under consideration in time  $t$  is better, the same, or poorer, compared with  $t - 4$ .

The forward-looking questions (e.g. Q2P) all have the following format: "(Expected development in next quarter) Compared with the same quarter of a year ago, will general business conditions



be: better, the same, or poorer?” As with the questions on current conditions, these questions ask whether the factor under consideration in time  $t + 1$  is expected to be better, the same, or poorer, compared with  $t - 3$ . Responses are relative to the same quarter of the previous year, which corresponds with year-on-year growth rates.

Although the survey questions imply that seasonal adjustment is not required, a common challenge is that respondents may not use the correct reference period when answering the question (Organisation for Economic Co-operation and Development, 2003). For example, answers to the forward-looking questions may compare expected outcomes in the next quarter  $t + 1$  with period  $t$ , instead of with period  $t - 3$ . In many cases, the time series of balances show some residual seasonality. The indicators are therefore adjusted for seasonality (United Nations, 2015).

As discussed above, confidence indicators are almost always based on balance statistics, which present a single figure summarising the responses of all participants to a particular question (Santero and Westerlund, 1996). It is the cross-sectional mean of survey responses if the standard quantification system is used: ‘better’ is quantified by +1, ‘the same’ by 0, and ‘poorer’ by -1. Confidence in period  $t$  relating to current conditions  $C_t^0$ , and confidence in period  $t$  relating to expected conditions  $C_t^1$ , may be defined as:

$$C_t^0 = \frac{1}{W_t} \sum_{i=1}^N w_{it} E_t f(\Delta^4 Y_{i,t})$$

$$C_t^1 = \frac{1}{W_t} \sum_{i=1}^N w_{it} E_t f(\Delta^4 Y_{i,t+1}),$$

where  $Y_{i,t+k}$  is again a measure of real activity at time  $t + k$  for firm  $i = 1, \dots, N$ ;  $\Delta^h Y_{i,t+k} = Y_{i,t+k} - Y_{i,t+k-h}$  for firm  $i$ ;  $w_{it}$  is the weight that each firm  $i$  receives at time  $t$ ; and  $W_t = \sum_{i=1}^N w_i$  is the sum of the weights.

The weights are calculated as:  $w_{it} = f_{it} s_{jt} / F_{jt}$ , where  $f_{it}$  the firm size weight (i.e. the inner weight reflecting turnover or number of employees) for firm  $i$  at time  $t$ ;  $s_{jt}$  is the subsector weight (i.e. the outer weight reflecting the share of total value added) for subsector  $j$  at time  $t$ ; and  $F_{jt} = \sum_{i=1}^N f_{it}$  is the total firm weight for subsector  $j$  at time  $t$ . These weights are equivalent to an explicit two-step weighting procedure, whereby weighted means are calculated for each subsector separately (using firm size weights), and then aggregated with the subsector weights (United Nations, 2015). The BER uses similar weights, except that they equal the product of firm and subsector weights  $w_{it} = f_{it} s_{jt}$ , without dividing by the total firm weight for the subsector  $F_{jt}$ .

The weighted means are calculated for each question separately. The BER business surveys contain a number of questions that may be useful in gauging business sentiment in South Africa. These include questions on general business conditions, production, orders placed, employment, and profitability. Most international institutions calculate composite confidence indicators by combining the responses to a number of questions (European Central Bank, 2013). Composite indicators react to various sources of economic fluctuations, while being resilient to fluctuations affecting single components. They may therefore exhibit fewer false alarms and fewer missed turning points than indicators based on a single question.

This chapter therefore combines the responses to a number of questions in the BER surveys to calculate composite indicators. For consistency, the composite indicators are derived from questions that are present in most of the sectoral business surveys. Table 2 reports the questions included in each of the sectoral surveys. These questions cover six types of variables, namely business

Table 2: Survey questions used by sector

Survey Question	Manufacturing	Construction	Trade	Services
Business Conditions	X	X	X	X
Activity	X	X	X	X
Employment	X	X	X	X
Profitability		X	X	X
Orders Placed	X		X	

conditions, activity (production or sales), orders placed, employment, and profitability. The measure of confidence about current conditions also include the question (Q1) on business satisfaction used to calculate the BER BCI. The composite sectoral indicators are calculated as the average of the weighted balances for the questions for each sector, as reported in Table 2. The results are similar if the different questions are combined using principal components rather than averages. The sectoral indicators are then weighted by GDP share to form the overall aggregate composite indicators (United Nations, 2015).

#### 4.1.1 Weights

Firm size weights were recorded by the BER for all respondents. The firm size weights are divided into nine categories. In this chapter, these firm size weights are applied to all the responses in all of the subsectors. In contrast, the BER uses exponential firm weights based on the nine categories, except for the building and motor vehicle surveys, where no weights are applied.

The subsector weights for the manufacturing, retail and wholesale subsectors are updated periodically by the BER, based on the composition of production or sales in each subsector, as calculated by StatsSA. Subsector weights are not recorded for the construction, motor vehicle and services sectors. The BER Building BCI is based on the unweighted responses for contractors only. The BER Motor Vehicle BCI does not receive a subsector weighting and the BER does not publish a Services BCI. In this chapter, the relative subsector weights for the construction, motor vehicle and services sectors are set equal to the average number of respondents for each subsector over the period. The results are similar when using an equal weighting procedure. GDP share weights are used in aggregating the four sector indicators to calculate the aggregate indicators. The BER BCI, in contrast, uses a simple equal weighted average of the sectoral indicators for manufacturing, contractors, retail, wholesale, and motor vehicles.

Experience has shown that the balances are not very sensitive to the choice of weighting procedure (Organisation for Economic Co-operation and Development, 2003). In this case the specific weighting procedure adopted does not significantly alter the results. Indeed, the unweighted versions of the indicators, calculated by stacking all of the available responses from the surveys are similar to the weighted versions. This confirms the findings by Kershoff (2015), who showed that the balance statistics were not sensitive to the use of the following alternative weighting procedures: a different allocation of firm size weights; the introduction of dynamic individual weights to provide for changes in response patterns; the application of a two-step weighting procedure; the inclusion of latecomers to increase the number of responses; and the use of different sector size weights for export variables.

## 4.2 The Impact of Confidence

As many economic variables move together over time, without an obvious causal direction, it can be challenging to identify the directions of relationships. In the literature, timing has often been relied on for identification. In this chapter, the literature (e.g. Taylor and McNabb (2007) and Barsky and Sims (2012)) is followed in using standard recursive VARs to trace out the dynamic responses of economic activity to surprise shocks in confidence. The aim is to investigate whether the indicators have a significant dynamic relationship with real output, whether they contain predictive content for output growth, and whether shocks to confidence generate responses that are in line with the findings in the literature, even after controlling for other economic variables.

The relationship are investigated for the aggregate variables, as well as separately for each sector, using bivariate recursive VARs featuring a measure of confidence and real GDP growth. In the bivariate VAR, both variables are treated as endogenous:

$$\begin{aligned}y_t &= \beta_{10} - \beta_{12}z_t + \gamma_{11}y_{t-1} + \gamma_{12}z_{t-1} + \epsilon_{yt} \\z_t &= \beta_{20} - \beta_{21}y_t + \gamma_{21}y_{t-1} + \gamma_{22}z_{t-1} + \epsilon_{zt},\end{aligned}$$

where  $y$  is output,  $z$  is confidence, and  $\epsilon$  is the residual of each equation.

A range of VARs are estimated for the quarterly data running from 1992Q1 to 2016Q3. The indicators enter in levels, while the real GDP series enter as annual quarter-on-quarter growth rates, e.g. 2015Q1 over 2014Q1, which corresponds with the survey reference period. Unit root tests indicate that virtually all of the aggregate and sectoral indicators, and the real GDP growth rates are stationary. The exception is real GDP growth in the services sector, which may be due to the shorter sample period. The appropriate number of lags are selected by means of the Akaike information criterion (AIC), the Schwarz criterion (SC) and the Hannan-Quinn criterion (HQ). The most parsimonious model is selected, provided that the diagnostic tests are satisfied (i.e. no serial correlation, homoscedasticity and normality). In the majority of cases, the information criteria point to two lags. The model fit is best when a constant term is included.

The confidence indicators 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 output, but shocks to output have no contemporaneous impact on confidence ( $\beta_{21} = 0$ ). In other words, innovations to the confidence indicators influence economic output on impact, but not vice versa. This is the identification strategy and ordering used in the literature (e.g. Leduc and Sill (2013), Girardi and Ruiter (2015), and Baker, Bloom and Davis (2015)). It can be motivated by the timing of the surveys before the release of most macroeconomic data (Leduc and Liu, 2012). When the survey is completed in time  $t$ , the respondents do not know the realisations of output growth in time  $t$ , as the response deadline is generally the second month of the quarter.

## 5 Results

This section presents the composite sectoral and aggregate business confidence indicators for South Africa. Simple linear interpolation is used for the few missing quarters. The indicators are evaluated according to their comovement with real GDP growth (i.e. their tracking record), to assess whether they improve on the existing indicators. Their turning points are then compared to the official SARB turning points, to assess their usefulness as leading indicators of the business cycle.

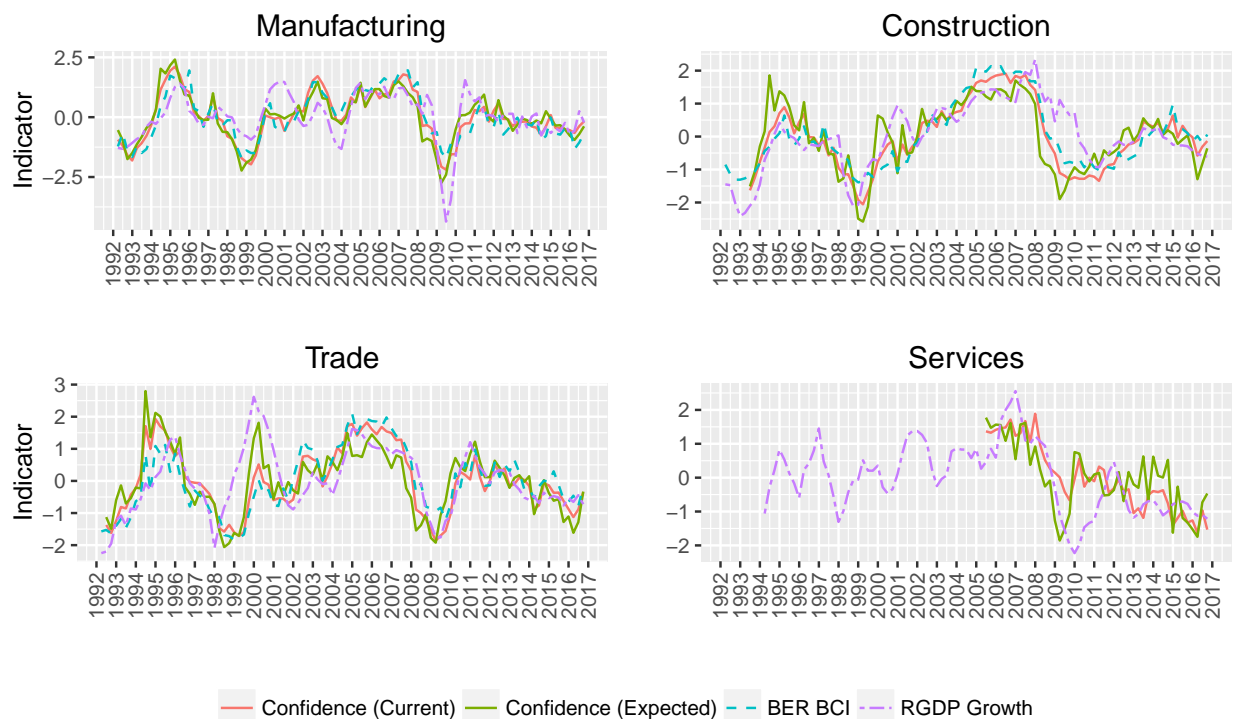


Figure 1: Sectoral confidence indicators compared to real sectoral GDP growth

## 5.1 Confidence Indicators

Figure 1 illustrates the weighted composite confidence indicators on current and expected conditions for the four sectors. The indicators on expected conditions lead the indicators on current conditions in each of the sectors. This is what one would expect, given that the expected conditions indicators are based on forward-looking questions. The new indicators are compared with each sector's BER indicator and sectoral real GDP growth. Real GDP growth is calculated as annual quarter-on-quarter growth rates, which corresponds to the reference period in the BER surveys.

The indicators appear to capture cyclical movements in the sectors. In general, they display an increase in the early 1990s until just after the first Democratic Elections in 1994Q2. They show a sustained decrease from 1995 into the recession of 1997-1998, associated with the East Asian and Russian crises. After troughs around the start of 1999, the indicators increase up to the global financial crisis at the end of 2007. During this extended upswing phase, the manufacturing and trade sectors reflect the two ambiguous periods in 2001 and 2003, when contractions in the SARB leading and coincident indicators obliged an evaluation of possible reference turning points (Venter, 2005). The construction sector exhibited a particularly strong and sustained increase in confidence during this upswing phase, possibly due to the construction projects associated with hosting the FIFA World Cup.

The global financial crisis was followed by a large decline in the indicators for all of the sectors, which continued into the subsequent Great Recession. There was a relatively quick recovery in confidence in the manufacturing and trade sectors. Confidence in the construction sector showed a more gradual recovery, especially in confidence about current conditions. In the services sector,

confidence about current conditions showed a slight recovery and then continued to decline, whereas confidence about expected conditions was quite erratic. The indicators for the other sectors exhibit a gradual decrease from around 2012, continuing into the downswing phase at the end of the sample period.

Table 3 reports the contemporaneous correlations of the sectoral indicators and their respective sectoral real GDP growth rates. All the indicators are highly positively correlated with real GDP growth. For the most part, the current conditions confidence indicators display the best tracking record, with the highest correlation with the reference series. In this sense, they are an improvement on existing confidence indicators. The curious exception is the construction sector, where the BER Building BCI, which includes only building contractors, has the highest correlation.

Table 3: Correlations between sectoral confidence and real sectoral GDP growth

			Manufacturing		Construction	
	Confidence (Cur)	Confidence (Exp)	BER BCI	Confidence (Cur)	Confidence (Exp)	BER BCI
Confidence (Exp)	0.94***			0.89***		
BER BCI	0.92***	0.85***		0.94***	0.75***	
RGDP Growth	0.68***	0.68***	0.61***	0.74***	0.56***	0.76***
			Trade		Services	
	Confidence (Cur)	Confidence (Exp)	BER BCI	Confidence (Cur)	Confidence (Exp)	BER BCI
Confidence (Exp)	0.87***			0.76***		
BER BCI	0.90***	0.72***				
RGDP Growth	0.61***	0.59***	0.56***	0.76***	0.57***	

Figure 2 illustrates the new aggregate confidence indicators, the BER and SACCI BCIs, as well as real GDP growth. The indicators appear to be strongly pro-cyclical, and follow real GDP growth closely. The shaded areas denote the recessionary periods according to the official turning points of the SARB. The indicators appear to match the different phases of the business cycle relatively well. Turning points are generally before the official turning points, as is discussed in more detail below.

The indicators exhibit an increase following the recession of the early 1990s, with peaks around 1995. There is a prolonged decrease into the recession of 1997-1998, and a strong recovery just before the official trough in 1999. Both ambiguous periods are reflected in moderate decreases in the indicators in 2001 and 2003. Both indicators exhibit a significant decrease following the global financial crisis in 2007, and a relatively mild recovery just before the official trough in 2009. The indicators are relatively flat during the last upswing phase (2010-2013) and decrease gradually during the downswing phase at the end of the sample period. The survey-based confidence indicators therefore appear to be plausible and potentially useful indicators of business confidence in South Africa.

Table 4 reports the contemporaneous correlations of the indicators and real GDP growth. Growth rates in the SACCI BCI are used to remove unit roots and are calculated as annual quarter-on-quarter growth rates. All the indicators exhibit a significant positive correlation with one another and with real GDP growth. The current conditions confidence indicator exhibits a higher contemporaneous correlation with real GDP growth than the BER BCI or SACCI BCI, which are also based on current conditions. The confidence measure of expected conditions leads GDP growth, and exhibits the highest correlation coefficient when lagged by one period. The results suggest that the indicators are all potentially useful leading or quasi-leading indicators of real activity.

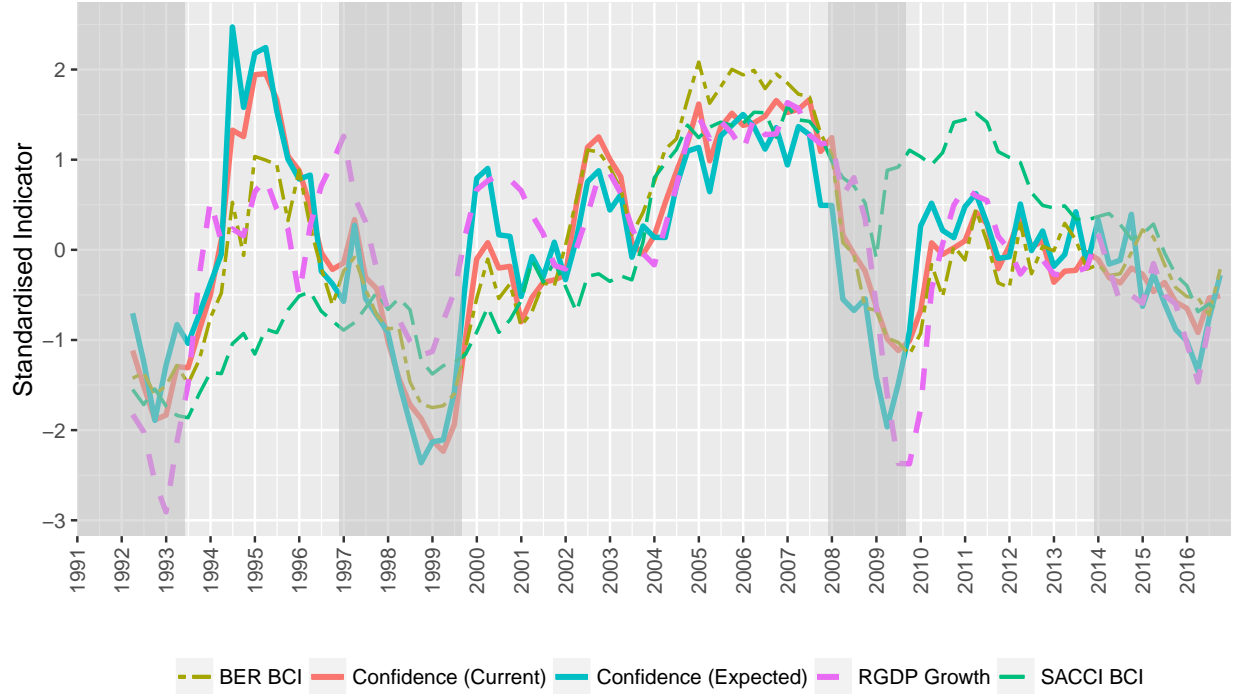


Figure 2: Aggregate confidence indicators compared to real GDP growth

Table 4: Correlations between confidence indicators and real GDP growth

	Confidence (Current)	Confidence (Expected)	BER BCI	SACCI Growth
Confidence (Current)				
Confidence (Expected)	0.92***			
BER BCI	0.93***	0.82***		
SACCI Growth	0.35***	0.48***	0.30***	
Real GDP Growth	0.78***	0.70***	0.75***	0.24**

### 5.1.1 Turning points

An accurate leading indicator should show general conformity to economic activity (i.e. a high correlation), as well as a consistent matching of turning points with the reference cycle. Although there are too few cycles over the sample period to analyse cyclical turning points in full detail, it is still of interest to assess whether the indicators behave in a systematic way around turning points. In other words, do they systematically lead, coincide with, or lag business cycle turning points.

The turning points in the indicators are determined with the so-called Bry-Boschan method. This is a non-parametric dating algorithm that automates the Burns & Mitchell approach to determining classical turning points (Bry and Boschan, 1971). The algorithm identifies local minima (troughs) and maxima (peaks) in a single time series. Censoring rules in the algorithm ensure that phases and cycles have a minimum duration. The algorithm has the advantage that it is a simple, transparent, easily replicable, and provides intuitively appealing results (Du Plessis, 2006). A variant of this algorithm for dealing with quarterly data, called the BBQ method, was developed by Harding and Pagan (2002). Following their suggestion, a censoring rule based on a minimum of two quarters for each phase and five quarters for a full cycle is applied.

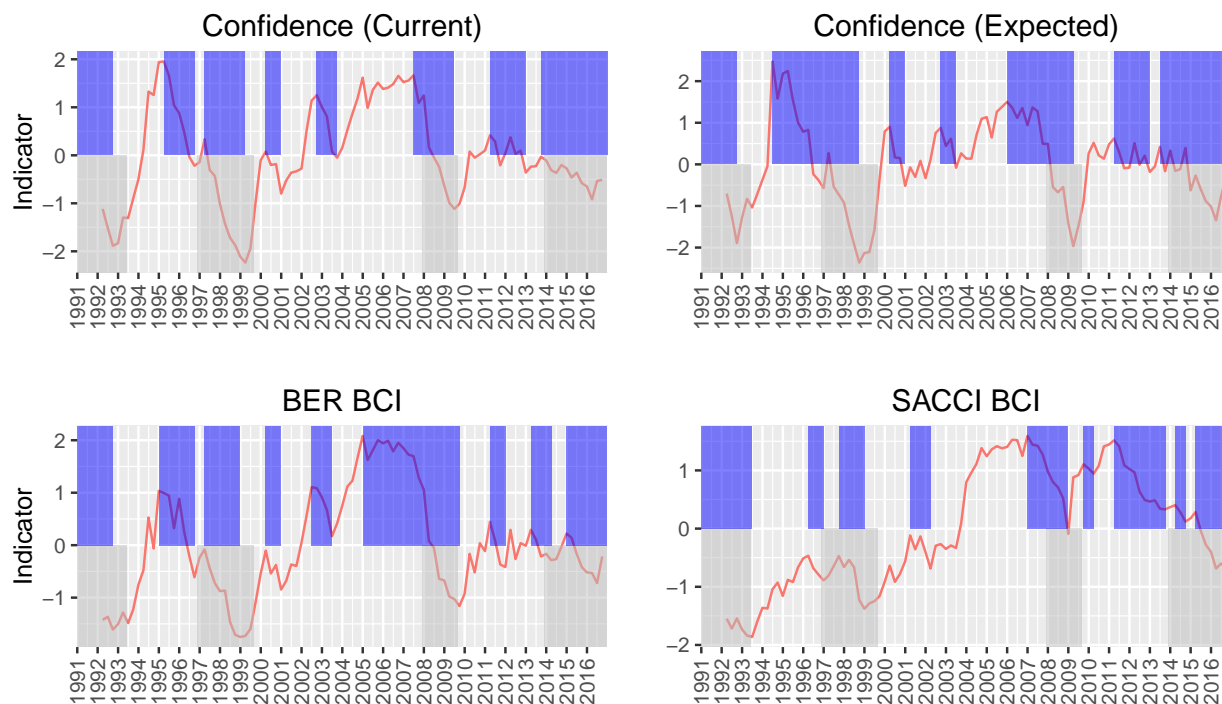


Figure 3: Confidence indicator turning points compared to the official SARB turning points

The resulting phases are illustrated in Figure 3, with the recessionary periods shaded. The top panel of each graph illustrates the turning points of the confidence indices, while the bottom panel of each graph shows the official SARB reference turning points. The sample period includes three upswing phases and four downswing phases. In addition, in 2001 and 2003 the SARB indicators pointed to possible reference turning points. Although the SARB dating committee decided at the time that neither of these periods qualified, subsequent data revisions have shown that in hindsight there could have been official peaks, especially in 2003, if the dating procedure had been followed mechanically (Venter, 2005).

The BBQ algorithm identifies eight recessionary periods in the current conditions confidence indicator and seven in the expected conditions confidence indicator. Four of these correspond to the official downswing phases. The turning points in the BER BCI and SACCI BCI are similar to those for the new confidence indicators. As the indicators are quite volatile, the default censoring rule produces a few recessions (or false positives) during the ambiguous period (2001 and 2003), and the last upswing phase (2012).

The indicators exhibit troughs before the three official trough dates, between one and four quarters before they occurred. The indicators exhibit peaks long before the official peak dates, in some cases as many as 12 quarters before they occurred. Therefore, the indicators provided advanced warning of turning points, albeit long before the official peaks. The false positives are problematic for the use of the indicators as early warning signals, implying that the indicators should be used in conjunction with other series, as in Laubscher (2014). Still, the reference series, real GDP growth, exhibits even more phases when dated with the BBQ method. Its cycles corresponded more closely with those of the indicators.

The comovement between these cycle phases can be measured with the concordance statistic suggested by Harding and Pagan (2002). The concordance statistic measures the comovement of two series, by considering the proportion of time the two series are simultaneously in the same phase. This entails testing whether  $I = Pr(S_{xt} = S_{yt})$  is close to 1, where  $S_{xt} = 1$  identifies an expansion in indicator  $x_t$ , and  $S_{yt} = 1$  identifies a business cycle upswing phase at time  $t$ . The statistic is calculated as follows:  $I = 1/T[\sum_{t=1}^T S_{xt}S_{yt} + \sum_{t=1}^T (1 - S_{xt})(1 - S_{yt})]$ . Following Harding and Pagan (2006), statistical significance is calculated with heteroskedasticity and autocorrelation consistent standard errors.

Table 5 reports the concordance statistics for the phases of the indicator variables, compared with the official SARB reference turning points. The indicators all exhibit significant concordance with the official SARB business cycle. The current conditions indicator has the highest concordance statistic with the official SARB cycle out of all the indicators, which occurs when it is lagged by one quarter, i.e. it leads the official cycle by one quarter. In this sense, it is an improvement on the existing indicators. The other three measures have the highest concordance statistics when they are lagged by two quarters, i.e. when they lead the official SARB cycle by two quarters.

Table 5: Concordance statistics with the SARB business cycle

	Confidence (Current)	Confidence (Expected)	BER BCI	SACCI BCI
lag=0	0.697***	0.596**	0.5556	0.6263*
lag=1	0.7071***	0.6465***	0.5859*	0.6566***
lag=2	0.6768***	0.6566***	0.6162**	0.6869***
lag=3	0.6263**	0.6465***	0.5859**	0.6667***

The composite current conditions confidence indicator therefore appears to be an improvement on existing confidence indicators in that it has a higher correlation with GDP growth and a higher concordance statistic with the official SARB business cycle.

## 5.2 The Impact of Confidence

In this section, the relationship between confidence and real economic activity in South Africa is further examined, including the timing of this relationship, and the extent to which correlation is conditional on other economic variables. A simple bivariate VAR is estimated to investigate the dynamic effects of confidence shocks on the economy. An extended VAR is then estimated to examine whether the results hold after the inclusion of additional variables.

### 5.2.1 Bivariate VAR Analysis

Impulse response functions (IRFs) can be generated to illustrate the dynamic impact of a shock to confidence on the system. The shock is an innovation to the residual in the equation. Figure 4 illustrates the IRFs of a bivariate VAR for the confidence indicator on current conditions and real GDP growth. The left panel plots the responses of real GDP growth to an orthogonal shock in the indicator, with 95% bootstrap confidence intervals.

Following an increase in confidence, real GDP growth increases by around 0.3% on impact, with a peak at two quarters. The impact on the growth rate is transitory, dying out after approximately seven quarters. This is equivalent to a permanent increase in the level of output, which confirms the findings in the literature (e.g. Barsky and Sims (2012)). The right panel plots the response of



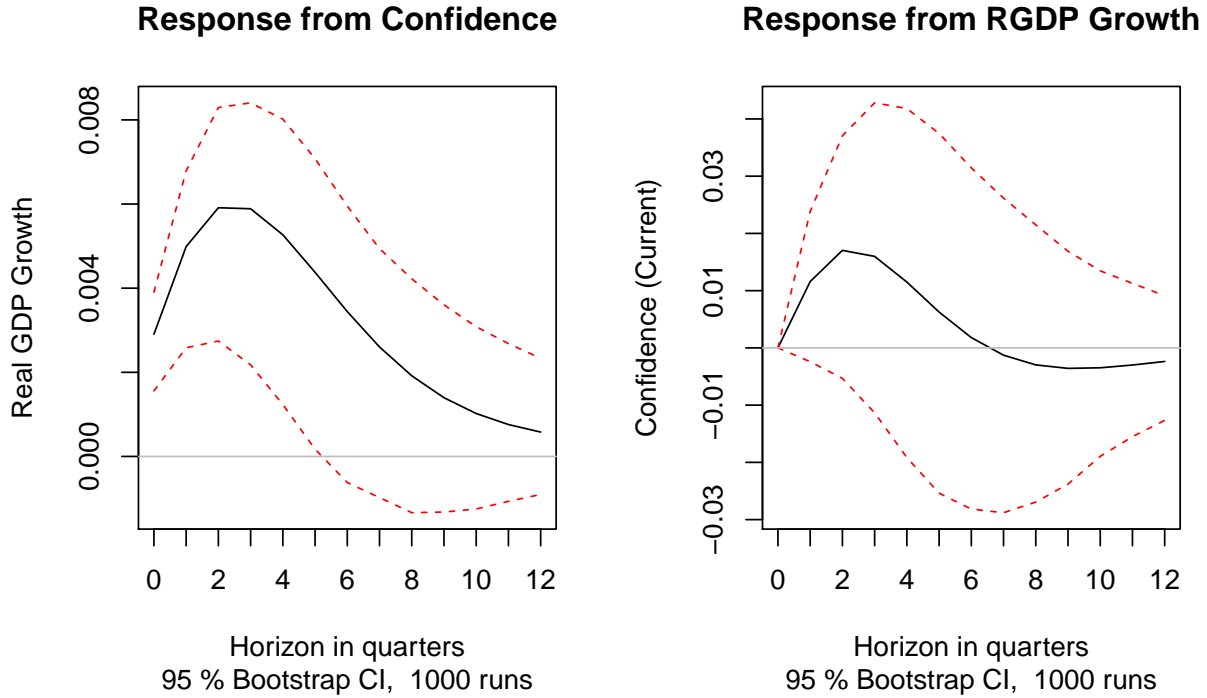


Figure 4: IRFs of confidence (current conditions) and real GDP growth

confidence to an orthogonal shock in real GDP growth. Following an increase in real GDP growth, there is an insignificant increase in confidence of around 2% after two quarters. The results are virtually identical for the expected conditions confidence indicator and the BER BCI, whereas the SACCI growth rate exhibits a smaller significant relationship with real GDP growth after two quarters. The results are similar for alternative orderings.

The importance of innovations can also be examined with variance decompositions. The forecast error variance decomposition (FEVD) shows the proportion of the movements in a sequence due to its own shocks and shocks to the other variable. Figure 5 illustrates the FEVDs for the current conditions confidence indicator and real GDP growth. Up to around half (46%) of the movements in real GDP growth are explained by the confidence indicator over the longer term, while real GDP explains up to 2% of the variance in the confidence indicator.

The results for the sectoral indicators are very similar to the aggregate results, with the exception of the construction sector, where the impact of a shock to confidence on GDP growth does not die out within the forecast horizon of 12 quarters.

Though instructive, the results from a bivariate system are prone to misspecification (Girardi and Ruiters, 2015). A larger VAR system is estimated to test the robustness of the relationships. The extended VAR includes the variables suggested by Redl (2015) for South Africa: confidence, the JSE All Share Index, the yield spread (i.e. the Government Bond Yield minus the three-month T-Bill rate), an employment index, and growth in real GDP, industrial production, and investment. These variables are typically included in the literature (e.g. Leduc and Sill (2013), Bachmann, Elstner and Sims (2013), and Baker, Bloom and Davis (2015)).

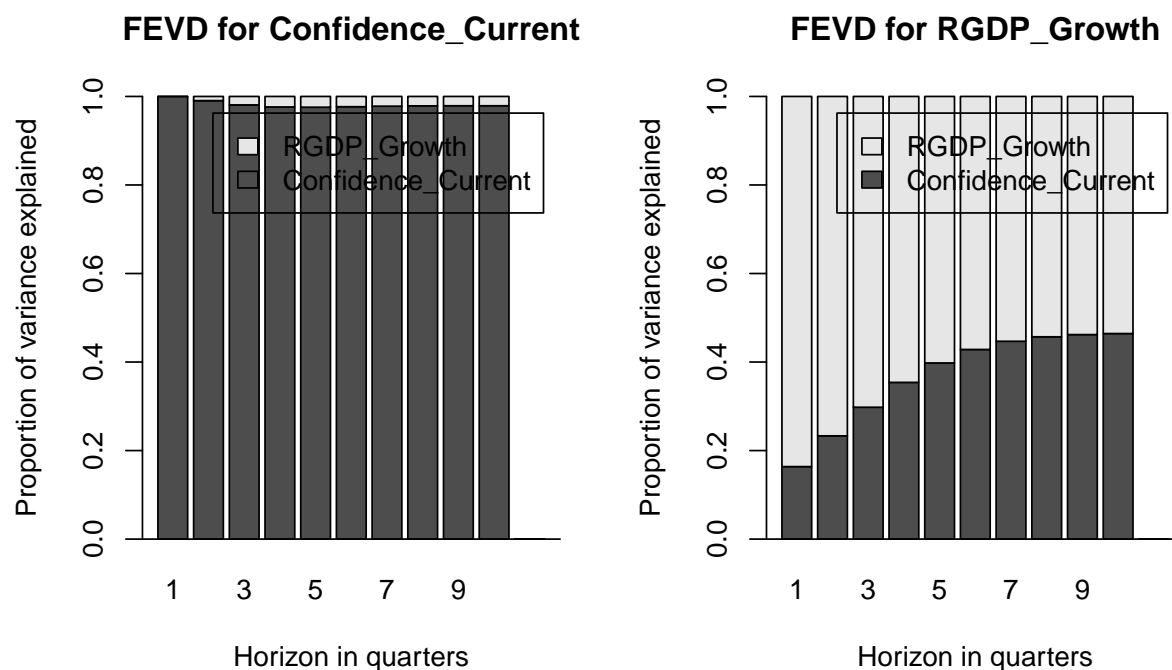


Figure 5: FEVDs of confidence (current conditions) and real GDP growth

The confidence indicator is ordered first, the financial variables next, and the real variables last. The financial variables are expected to move faster than the real variables (Redl, 2015). An alternative ordering of placing the confidence indicator last provides qualitatively similar results. As was the case with the previous VAR, the variables enter as real annual quarter-on-quarter growth rates, except for confidence and the yield spread.

The IRFs for the impact of confidence on real GDP, production, employment and investment growth are illustrated in Figure 6. In this larger system, a shock to confidence leads to a significant impulse responses in all four variables. The larger system provides similar results to the bivariate VAR in terms of the responses of real GDP growth. The responses of real employment growth are similar in magnitude to real GDP growth, while the responses of real production and investment growth are larger. According to the FEVD, confidence explains around 30%, 20%, 30%, and 35% of the variance in the growth rates in real GDP, production, employment and investment.

## 6 Conclusion

This chapter has estimated new proxies for business confidence in South Africa, using micro-data from the BER business tendency surveys, with the aim of improving on the existing measures. Two sets of composite confidence indicators were calculated as the weighted cross-sectional mean of responses to questions on current and expected future business conditions. The composite current conditions confidence indicator appeared to be an improvement on existing confidence indicators in that it exhibited a higher correlation with GDP growth and a higher concordance statistic with the official SARB business cycle.

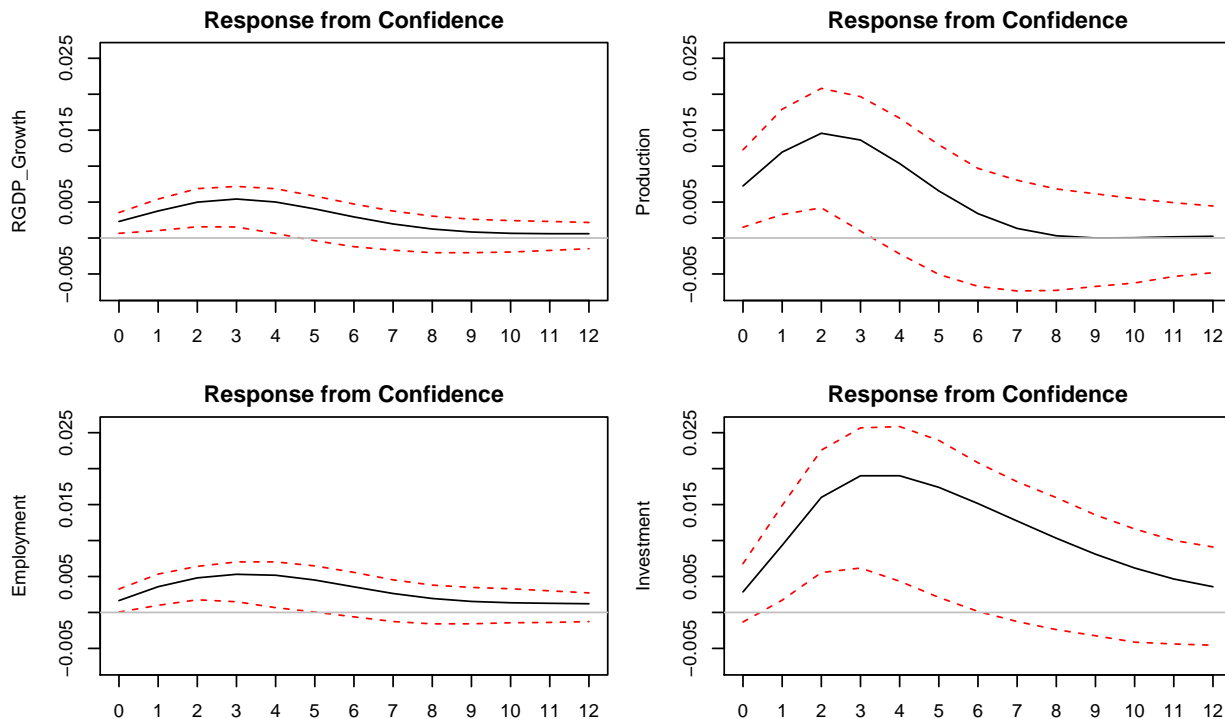


Figure 6: IRFs of real GDP, production, employment and investment growth to confidence shocks

The relationship between the business confidence indicators and real economic activity in South Africa was further examined. The aim was to study whether there was a significant positive relationship between the indicators and real GDP growth, the timing of this relationship, and whether it remained significant after taking other economic variables into account.

Overall, the results provided evidence at least of significant comovement between the sectoral and aggregate confidence indicators and real economic activity. The indicators had a positive and significant impact on real GDP growth in the VAR models. Shocks to the indicators accounted for a sizeable fraction of variation in economic activity. This was the case even after controlling for other economic variables in a larger VAR system. This implies that the confidence indicators contain useful predictive content for current and future economic developments. As a result, the confidence indicators may be useful for monitoring developments in a timely manner and for forecasting future economic activity.

## References

- Akerlof, G. and Shiller, R. J. (2015) *Animal Spirits: How Human Psychology Drives the Economy, and Why It Matters for Global Capitalism*. Princeton University Press.
- Bachmann, R., Elstner, S. and Sims, E. R. (2013) 'Uncertainty and Economic Activity: Evidence From Business Survey Data', *American Economic Journal: Macroeconomics*, 5(2), pp. 217–249.
- Baker, S. R., Bloom, N. and Davis, S. J. (2015) 'Measuring Economic Policy Uncertainty', *NBER*

*Working Paper*, 21633.

Barsky, R. B. and Sims, E. R. (2012) ‘Information, Animal Spirits, and the Meaning of Innovations in Consumer Confidence’, *American Economic Review*, 102(4), pp. 1343–1377. doi: 10.1257/aer.102.4.1343.

Beaudry, P. and Portier, F. (2004) ‘An Exploration into Pigou’s Theory of Cycles’, *Journal of Monetary Economics*, 51(6), pp. 1183–1216. doi: 10.1016/j.jmoneco.2003.10.003.

Bosch, A. (2015) ‘Composite Business Cycle Indicators for South Africa’, *South African Reserve Bank*, (24 March 2015).

Bry, G. and Boschan, C. (1971) ‘Programmed Selection Of Cyclical Turning Points’, *National Bureau of Economic Research*, I, pp. 7–63.

Carroll, C. D., Fuhrer, J. C. and Wilcox, D. W. (1994) ‘Does Consumer Sentiment Forecast Household Spending? If So, Why?’, *American Economic Review*, 84(5), pp. 1397–1408.

Cochrane, J. H. (1994) ‘Shocks’, *NBER Working Paper*, 4698.

Driver, C. and Urga, G. (2004) ‘Transforming Qualitative Survey Data: Performance Comparisons for the UK’, *Oxford Bulletin of Economics and Statistics*, 66(1), pp. 71–89. doi: 10.1111/j.1440-1754.2007.01273.x.

Du Plessis, S. (2006) ‘Reconsidering the Business Cycle and Stabilisation Policies in South Africa’, *Economic Modelling*, 23(5), pp. 761–774. doi: 10.1016/j.econmod.2005.10.006.

European Central Bank (2013) ‘Confidence Indicators and Economic Developments’, *ECB Monthly Bulletin*, (January), pp. 45–58.

Gayer, C., Girardi, A. and Reuter, A. (2014) ‘The Role of Survey Data in Nowcasting Euro Area GDP Growth’, *European Commission Economic Papers*, 538(December). doi: 10.2765/71951.

Girardi, A. and Ruiter, A. (2015) ‘New Uncertainty Measures for the Euro Area Using Survey Data’, *Lwiss LAB of European Economy: European Commission*, pp. 1–43.

Harding, D. and Pagan, A. (2002) ‘Dissecting the Cycle: A Methodological Investigation’, *Journal of Monetary Economics*, 49(2), pp. 365–381. doi: 10.1016/S0304-3932(01)00108-8.

Harding, D. and Pagan, A. (2006) ‘Synchronization of Cycles’, *Journal of Econometrics*, 132, pp. 59–79. doi: 10.1016/j.jeconom.2005.01.023.

Kabundi, A. (2004) ‘Estimation of Economic Growth in France Using Business Survey Data’, *IMF Working Paper*, WP/04/69.

Kabundi, A., Nel, E. and Ruch, F. (2016) ‘Nowcasting Real GDP Growth in South Africa’, *ERSA Working Paper*, 581.

Kershoff, G. (2000) ‘Measuring Business and Consumer Confidence in South Africa’, *Bureau for Economic Research*, (December).

Kershoff, G. (2002) ‘An Analysis of The BER’s Trade and Building Survey Panels’, *Journal for Studies in Economics and Econometrics*, 26(1), pp. 1–17.

Kershoff, G. (2015) ‘South Africa: The BER’s Business Tendency Surveys’, *Bureau for Economic*

*Research*, pp. 1–19.

Keynes, J. M. (1936) *General Theory of Employment, Interest and Money*. London: Macmillan. doi: 10.2307/2143949.

Kilic, E. and Cankaya, S. (2016) ‘Consumer Confidence and Economic Activity: A Factor Augmented VAR Approach’, *Applied Economics*, 48(32), pp. 3062–3080. doi: 10.1080/00036846.2015.1133902.

Laubscher, P. (2014) ‘A New Recession-Dating Algorithm for South Africa’, *Stellenbosch Economic Working Papers*, 06/14.

Leduc, S. and Liu, Z. (2012) ‘Uncertainty Shocks are Aggregate Demand Shocks’, *Federal Reserve Bank of San Francisco Working Paper*, 2012-10.

Leduc, S. and Sill, K. (2013) ‘Expectations and Economic Fluctuations: An Analysis Using Survey Data’, *Review of Economics and Statistics*, 95(October), pp. 1352–1367.

Ludvigson, S. C. (2004) ‘Consumer Confidence and Consumer Spending’, *Journal of Economic Perspectives*, 18(2), pp. 29–50.

Matheson, T. (2007) ‘An Analysis of the Informational Content of New Zealand Data Releases: The Importance of Business Opinion Surveys’, *Reserve Bank of New Zealand: Discussion Paper Series*, DP2007/13(September).

Mendicino, C. and Punzi, M. T. (2013) ‘Confidence and Economic Activity: The Case of Portugal’, *Banco de Portugal*, (Winter), pp. 39–49.

Nardo, M. (2003) ‘The Quantification of Qualitative Survey Data: A Critical Assessment’, *Journal of Economic Surveys*, 17(5), pp. 645–668.

Organisation for Economic Co-operation and Development (2003) *Business Tendency Surveys: A Handbook*. Edited by E. Giovannini and E. Burgeat. Paris, France: OECD Publications.

Parigi, G. and Golinelli, R. (2004) ‘Consumer Sentiment and Economic Activity’, *Journal of Business Cycle Measurement and Analysis*, 2004(2), pp. 147–170. doi: 10.1787/jbcm-a-v2004-art10-en.

Pellissier, M. (2002) ‘Business Confidence and the South African Business Cycle’, *Journal for Studies in Economics and Econometrics*, 26(2), pp. 51–67.

Redl, C. (2015) ‘Macroeconomic Uncertainty in South Africa’, *ERSA Working Paper*, 509.

SACCI (2011) ‘Updated and Revised SACCI Business Confidence Index’, *South African Chamber of Commerce and Industry*.

Santero, T. and Westerlund, N. (1996) ‘Confidence Indicators and Their Relationship to Changes in Economic Activity’, *OECD Economics Department Working Papers*, 170. doi: 10.1787/537052766455.

Taylor, K. and McNabb, R. (2007) ‘Business Cycles and the Role of Confidence: Evidence for Europe’, *Oxford Bulletin of Economics and Statistics*, 69(2), pp. 185–208. doi: 10.1111/j.1468-0084.2007.00472.x.

United Nations (2015) *Handbook on Economic Tendency Surveys*. New York: United Nations Publications.

Van Aarle, B. and Kappler, M. (2012) ‘Economic Sentiment Shocks and Fluctuations in Economic

Activity in the Euro Area and the USA', *Intereconomics*, 47(1), pp. 44–51. doi: 10.1007/s10272-012-0405-z.

Venter, J. C. (2005) 'Reference Turning Points in the South African Business Cycle: Recent Developments', *SARB Quarterly Bulletin*, (September), pp. 61–70.