Business Sentiment and the Business Cycle in South Africa

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This paper uses the microdata from the BER's business tendency surveys to calculate indicators of business sentiment for South Africa. Various measures of confidence and uncertainty are calculated from the early 1990s for the five sectors surveyed by the BER and these are then aggregated to form overall indicators. The survey-based measures seem to be plausible indicators of confidence and uncertainty in South Africa. They are then compared to measures of real economic activity, including output, employment and investment. The relationships are investigated using agnostic VARs and impulse response functions. The preliminary findings indicate that all the measures of confidence are significantly positively correlated with economic activity. Further analysis could potentially investigate whether these measures of confidence are useful for forecasting and as leading indicators of the business cycle. The survey-based measures of uncertainty do not exhibit the typical anti-cyclical trend found in the literature. Instead, large increases in these measures tend to occur around the start of each recovery phase of business cycle.

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1 Introduction

This paper examines the relationship between business sentiment and real activity in South Africa. Two concepts are commonly referred to in the context of business sentiment: *confidence* and *uncertainty*. Business confidence involves economic agents' perceptions of the current and expected future business climate. This is dependent on the prevailing economic environment and expectations of future prospects. Uncertainty reflects agents' inability to forecast the probability of future events occurring. It entails a lack of knowledge of the set of possible outcomes and the probability of each occurring.

The global financial crisis and subsequent Great Recession were associated with low levels of confidence and heightened uncertainty. According to the ECB (2013), the financial crisis created a climate of exceptionally low confidence and heightened uncertainty, which contributed to a large extent to the subsequent recession. Even the subsequent recovery was characterised by only modest improvements in business sentiment. This has motivated an increase in research on the impact of changes in business sentiment, and especially uncertainty, on real activity.

Macroeconomic theory postulates a causal link between confidence and economic activity, based on multiple equilibria in which self-fulfilling expectations of subjective agents generate changes in real activity. Yet the empirical evidence on the relation between confidence and economic activity is inconclusive (Taylor and McNabb, 2007). Recent work suggests that changes in confidence may affect long-run output growth rather than cause short-run fluctuations (Barsky and Sims, 2012). Even if confidence measures do not hold distinct short-run information, their leading indicator

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properties are well-established and their timely availability has made them popular with analysts all over the world. This is also the case in South Africa, where the Bureau for Economic Research's (BER) business confidence index is used by the SARB as a leading indicator to identify the official business cycle turning points.

The recent literature has focused particular attention on the effects of changes in uncertainty on economic activity. While the consensus in the literature is that uncertainty rises during recessions or economic crises, the precise impact of uncertainty on the real economy, and how it differs from low levels of confidence, is less clear. Bloom (2009) suggested a "wait-and-see" effect for uncertainty shocks, which would provide a channel through which uncertainty could exogenously influence production, employment and investment, thereby driving business cycles. However, a number of channels have been proposed through which uncertainty could potentially have negative or positive effects on growth (Bloom, 2014).

This ambiguity is present in the empirical literature. This may be due to the difficulties surrounding the measurement of uncertainty and the identification of separate causal effects. Some of the recent work has suggested that increases in uncertainty may generate fluctuations in output, which would have important policy implications for issues like the appropriate size of stimulus packages in periods of heightened uncertainty. However, it is not yet clear whether uncertainty itself has an impact on the business cycle or whether it is an epiphenomenon which occurs during recessions or periods of low confidence. Hence, there is a need to further examine the effect of uncertainty on the real economy.

This paper studies the relationship between sentiment and economic activity in South Africa using the BER's business tendency surveys. Although measuring economic sentiment is not a straightforward task, survey-based indicators can be helpful in discovering agents' opinions on future economic developments. Survey-based measures may include information known by the respondents but not yet reflected in aggregate economic variables. Thus, they may reveal important information about expectations, particularly regarding waves of optimism or pessimism, which may be drivers of the business cycle. Moreover, these indicators are often available earlier (with a shorter lag) than official statistics and are usually not subject to revisions (ECB, 2013).

The aim is to construct different measures of business sentiment based on the microdata from the BER business tendency surveys. Indicators of confidence and uncertainty are calculated at sectoral level and in the aggregate. The relationships between these sentiment indicators and economic activity over the cycle are then evaluated, using the standard agnostic econometric methods (VARs) employed elsewhere. The aim is to examine whether these survey-based measures of confidence and uncertainty have unique and distinguishable relationships with real economic activity. It may be particularly useful to examine the impact of sector-specific sentiment indicators, where the relationships might show up more clearly than in aggregate indicators (INIS, 2014).

It is important to confirm the existence and nature of the relationship between sentiment and economic activity in settings outside of the developed world. Developing countries are often characterised by higher business uncertainty than developed countries (Bloom, 2014). The South African economy in particular has been subject to much higher levels of political and economic uncertainty than developed economies. Not only is South Africa an emerging market, but its tumultuous political history and the legacy of Apartheid has contributed significantly to business uncertainty. An investigation of sentiment in the developing country context might therefore be especially informative.

2 The Concepts of Confidence and Uncertainty

Within the context of business sentiment, the two concepts which are commonly referred to are business confidence and uncertainty. Pellissier (2002) described business confidence as the *"degree of sentiment towards risk taking by business for whatever reason."* Business confidence involves the state of mind of agents regarding the current and expected future business climate. It can be interpreted a function of agents' perceptions of prevailing business conditions, as well as their expectations of future events.

Knight (1921) defined uncertainty as *"people's inability to forecast the likelihood of events happening."* Uncertainty entails a lack of knowledge regarding the set of possible outcomes and the probability of each occurring (e.g. the number of coins ever produced is uncertain). This lack of knowledge makes prediction increasingly difficult and uncertainty will therefore rise during unique circumstances. According to this definition, uncertainty is distinct from the concept of risk, which describes a known probability distribution over a set of events (e.g. a coin toss). Nevertheless, researchers usually refer to a single concept of uncertainty, which is typically a stand-in for a mixture of risk and uncertainty (Bloom, 2014).

The two concepts of confidence and uncertainty are inherently linked. Confidence could be low due to a combination of high uncertainty impairing the formation of expectations, coupled with a dissatisfaction regarding current conditions (Hart, 2015). Survey-based indicators for both are usually constructed from the first and second moments of responses to specific survey questions (often the same question).

3 Confidence

3.1 Theoretical Links

Notwithstanding the popularity of confidence indicators with analysts, the stance of the academic literature is more ambiguous. The opinions 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 little causal role, to the conclusion that they have no value, even in forecasting (INIS, 2014).

Broadly speaking, there are two contrasting approaches to the role of confidence in macroeconomics. The first view, which Barsky and Sims (2012) refer to as the "animal spirits" view, claims that independent changes in beliefs have causal effects on business cycles. This view is usually associated with consumer confidence, and the idea that a long-lasting negative consumption shock, associated with an exogenous shift in pessimism, can have a causal effect on overall aggregate demand.

The second view, which Barsky and Sims (2012) refer to as the "information" or "news" view, claims that confidence indicators contain information about current and future economic developments. The idea is that confidence can proxy for news that agents receive about future productivity that does not otherwise show up in econometricians' information sets. This view supposes that confidence innovations might contain predictive information when agents become aware of changes in future productivity that are independent of current productivity. Both views can be compatible with leading indicator properties, but only the animal spirits view would imply causality (ECB, 2013).

A theoretical causal link between business confidence and fluctuations in economic activity can be found in dynamic general equilibrium models that incorporate the subjective views of economic agents. These models give rise to multiple equilibria that are not determined by standard economic fundamentals and in which expectations about the future level of output can become self-fulfilling. As a result, a decline in business confidence can cause a decline in output. In other words, changes in confidence can cause changes in real activity, independently of economic fundamentals. However, the link need not necessarily be quantitatively significant. Thus, the impact of confidence on economic activity becomes an empirical issue (Taylor and McNabb, 2007).

3.2 Empirical Findings

There are two main challenges when it comes to empirical work on business confidence: how to construct proxies for confidence and how to measure the impact of confidence on real activity. Confidence is an elusive concept, which is difficult to define precisely or measure directly. In practice, analysts typically aggregate information from business and consumer surveys to construct proxies for confidence. These surveys usually contain a small number of qualitative questions, which can be answered quickly by respondents. Indicators are typically derived from the subjective answers to questions on past, current and expected future economic developments. The assumption is that before a specific business activity is implemented (e.g. new production plans, employment, or purchases), a certain opinion-building has taken place, which may be called "sentiment" or "confidence" (Santero and Westerlund, 1996). The most important advantage of these surveys is that they are available long before official statistical data become available. Moreover, they are not subject to revisions and are useful in avoiding trend and seasonality problems.

The first issue is to summarise or aggregate the survey responses. A very common and widely used method is to calculate so-called balances. In the context of business tendency surveys, balances are simple 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 implement and understand and are considered both practical and entirely adequate for cyclical analysis (OECD, 2003).[3]

Although balances are by far the most common aggregation method used by statistical agencies and analysts, they do rely on assumptions about the distribution of responses. Namely, that the "unchanged" share is constant over time and that the relationship among positive and negative answers is linear and constant over time. For this reason, various alternatives have been discussed in the literature, including the probabilistic approach, the regression approach, and the latent factor approach (INIS, 2014).[4] However, these approaches usually require actual quantitative measures of the relevant variables, which is very restrictive in the case of business confidence, where actual quantitative measures are not available. Moreover, the fact that they are linked to a reference series,

[3]Diffusion indices are a slight variation on balances. In the context of business tendency surveys, they indicate the degree to which the change is diffused throughout the sample. The most common way to calculate a diffusion index consists of taking the percentage of respondents answering positively and adding it to half of the percentage of respondents reporting "unchanged". Thus, diffusion indices are a linear transformation of balances and have the same information content (OECD 2003).

[4]The probability approach assumes a probability distribution for the variable concerned, which is required to infer the parameters of the probability distribution functions. The statistic is a linear combination of values deriving from a transformation of the observed frequency of the answers. The regression approach uses the relationship between actual values (measured by official statistics) and respondents' perception of the past (reported in the business surveys as judgements) as a yardstick for the quantification of respondents' expectations about the future. Thus, quantitative expectations are a function of a specific regression model rather than a specific probability distribution (Nardo 2003). The latent factor approach regards the percentages of each qualitative answer as a function of a common "latent measure" observed by respondent but not by econometricians.

implies that these methods can become unreliable when exceptional events have a large impact on the correlation between the survey data and the quantitative reference data (INIS, 2014).

The evidence suggests that sophisticated methods tend to produce indicators that follow the common cycle, which can be more easily deduced by simple aggregation methods such as balances. For instance, the Italian National Statistical Agency found a very high correlation between balances and more sophisticated indictors when three-option replies were used (OECD, 2003). Driver and Urga (2004) assessed different ways of converting qualitative data, obtained from the UK employers' business survey, into quantitative indices for a number of economic variables. The relationship between the observed actual values of six economic variables and the corresponding transformed survey responses was considered. They found that the balance statistic was a satisfactory method of transforming the questions on investment, output and exports.

The next issue concerns the types of questions that should be used to measure confidence, and whether combinations of indicators should be used to calculate aggregate measures. Business confidence entails the relative optimism or pessimism among firms regarding *current conditions* and expected *future developments*, with the former probably influencing the latter. The recent literature suggests a distinction between indicators of current activity and forward-looking indicators (Bachmann, Elstner and Sims, 2010).

Formally, one can define a k-period-ahead expectations measure of activity (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, down, or unchanged classification:

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

An alternative is to use a binary classification (e.g. satisfactory or unsatisfactory):

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

where a is determined by the preferences of the agent. The recent literature terms C_t^k a measure of "activity" when $k = 0$ and a measure of "confidence" when $k > 0$.

Various confidence indices have been used in the literature. For instance, Taylor and McNabb (2007) used an arithmetic average of two activity measures (based on questions on current conditions) and one confidence measure (based on a question on future conditions).[5] Bachmann, Elstner and Sims (2010) and Bachmann, Elstner and Sims (2013) defined two forward-looking indices and two indices of current activity, based on the Business Outlook Survey and the German Ifo Business Climate Survey.[6] Barsky and Sims (2012) constructed a forward-looking measure of confidence from the

[5]The business confidence indicator was the arithmetic average of results to the following questions: assessments of order book-levels; assessments of export order-book levels; and production expectations for the months ahead.

[6]The forward looking question in the BOS took the following form: *"General Business Conditions: What is your evaluation of the level of general business activity six months from now vs. [current month]: decrease, no change, increase?"* In the Ifo the question was: *"Expectations for the next three months. Our domestic production activities with respect to product XY will (without taking into account differences in the length of months or seasonal fluctuations): increase, roughly stay the same, decrease."* The question on current activity took the following form for the BOS: *"General Business Conditions: What is your evaluation of the level of general business activity [last*

balance of a question on expectations over the next five years.[7] According to this distinction the BER business confidence index, discussed in more detail below, is an index of current activity.

The construction of aggregate indicators raises question about the appropriate weighting of the individual components. Indicators from multiple sectors, in turn derived from multiple questions, are often employed. For example, the EC conducts qualitative business surveys for five different sectors, using questions on current conditions and expectations. The aggregate confidence index (the Economic Sentiment Index) is calculated as a weighted average (using value added shares) of sentiment in industry, services, retail trade and construction, as well as among consumers (ECB, 2013). Another example is the Ifo Business Climate Indicator, which is a prominent leading indicator for the German economy. It aggregates results for the manufacturing, construction, wholesaling and retailing sectors. The replies are weighted according to the importance of the industry. It is computed as a geometric mean of the balances referring to the current business situation and the business outlook in the next six months (INIS, 2014).

These survey-based indicators have performed quite well in now-casting and forecasting macroeconomic variables (Strasser and Wohlrabe, 2015), although the evidence has not been unanimous. The empirical literature has often investigated the extent to which confidence indicators contain information over and above economic fundamentals. In other words, studies have investigated whether confidence measures can predict economic outcomes, after the appropriate macroeconomic variables are taken into account (INIS, 2014).

Santero and Westerlund (1996) explored the empirical relationship between confidence indicators and output components. They found that sentiment measures from business surveys provided valuable information for the assessment of the economic situation and for forecasting, although to varying degrees across countries. They also found that business confidence indicators were much more useful than consumer confidence indicators for economic analysis.

Many of the studies have concentrated on consumer confidence when analysing the usefulness of such indicators as predictors of economic developments (ECB, 2013). Parigi and Golinelli (2004) investigated the forecast performance of consumer confidence for economic activity. For certain countries in their sample the results of both in-sample and out-of-sample tests confirmed the predictive power of the consumer confidence as a leading and coincident indicator.

Taylor and McNabb (2007) looked at the ability of confidence indicators to forecast GDP growth over and above existing leading indicators for four European economies. They found that across countries, both consumer and business confidence indicators generally exhibited good predictive power in identifying turning points in the business cycle. For example, for the UK a 1 percentage point increase in business confidence reduced the probability of a downturn by around 4 percentage points. The inclusion of confidence indicators also reduced the forecasting error associated with quantitative estimates for two of the countries in their sample (the UK and the Netherlands).

Barsky and Sims (2012) investigated the predictive ability of consumer confidence for macroeconomic variables such as real consumption and GDP. They found that the impulse responses of consumption and income to innovations in consumer confidence measures were significant, slow-building, and permanent. They concluded that consumer confidence was not merely noise, nor simply reflections

month] vs. [current month]: decrease, no change, increase?" And for the Ifo: *"Trends in the last month. Our domestic production activities with respect to product XY have (without taking into account differences in the length of months or seasonal fluctuations): increased, roughly stayed the same, decreased."*

[7] Their measure was based on the following question: *"Turning to economic conditions in the country as a whole, do you expect that over the next five years we will have mostly good times, or periods of widespread unemployment and depression, or what?"*

of information contained in other variables. This suggests that there is at least some truth to the "news" view of confidence. If confidence contained no news about future fundamentals and the relationship between confidence and subsequent activity reflected only "animal spirits", one would expect to see at most transitory responses of consumption and income to confidence innovations.

The lack of consistent results among the empirical studies may be linked to the different proxies used to measure confidence, as well as the different sets of economic indicators used in the various forecasting models. The distinction between current and forward-looking measures might also be important when evaluating this literature. The literature has often attempted to evaluate how publically-disseminated sentiment indices perform, rather than to construct appropriate proxies of sentiment from underlying data (often because the micro-data is unavailable). When the confidence index is a measure of current conditions or "activity", it might be more appropriate to evaluate the indicator's ability to capture real activity accurately, instead of predicting ΔY_{t+k}, with $k > 0$.

Another possible reason for the disagreement may be the use of a linear functional form. It may be that only abrupt shifts in confidence are relevant to signal changes real activity (e.g. only below a certain threshold, or only when significantly negative) (INIS, 2014). For example, ECB (2013) found that shocks to confidence played a relatively small role during normal times, compared to other economic variables. However, they played a more important role during episodes of economic tensions (financial crises or economic recessions) or geopolitical turmoil. For the Euro Area, the impact was asymmetric: large decreases in consumer confidence were more important in predicting future changes in consumption than large increases. This pointed to a non-linear and asymmetric relationship between confidence and economic fluctuations. The forecasting ability of confidence indicators might be completely offset by other indicators during ordinary times, while increasing notably in the presence of unusual events.

Even if confidence indicators are just a synthesis of traditional indicators, they might still be useful for monitoring economic developments in a timely manner and for now-casting (Parigi and Golinelli, 2004). This is because they are available earlier than official quantitative statistics and are subject only to limited revisions. The ECB (2013) argued that the strong correlations between confidence indicators and various economic and financial variables, imply that confidence indicators are useful in monitoring economic developments, as they are both timely and point to some leading properties with respect to official quantitative data, without necessarily implying any causal relationship.

In South Africa the BER's business confidence measure is used by the SARB as an official leading indicator of the business cycle. Pellissier (2002) examined the ability of two South African business confidence indicators (the BER and SACOB) as business cycle indicators. The business confidence indicators were highly correlated with each other and showed signs of having leading indicator properties. However, both the indicators seemed to be moving towards a coincident relationship rather than a leading one, and the BER indicator displayed comparable cyclical turning point attributes. More recently, Laubscher (2014) selected time series that were the closest predictors of the official reference business cycle turning points. He found that the BER business confidence index was a useful leading indicator.

4 Uncertainty

4.1 Theoretical Links

The theoretical literature emphasises two negative and two positive channels for uncertainty to influence growth. The largest body of theoretical literature focuses on the “real options” theory, based on Bernanke (1983). Uncertainty may have economic consequences when there is a degree of irreversibility to firms’ actions. Firms may choose to temporarily delay an investment if the returns to waiting exceed the returns to investing in the present period. Agents receive new information over time, reducing uncertainty and increasing their ability to undertake the optimal investment. If the value of time, i.e. the benefit of new information, exceeds the costs associated with committing to a suboptimal project, it is rational to wait before committing to an investment (Binding and Dibiasi, 2015). In the language of real options, the option value of waiting increases as the uncertainty increases (Bloom, 2014).

This theory has given rise to the idea of the “wait-and-see” effect (Bloom, 2009). If a firm faces large fixed adjustment costs[8], higher uncertainty over future demand makes new hiring and investment less attractive. Firms try to minimise the number of times this fixed adjustment cost must be paid. If the future is very uncertain, in the sense that demand could be either very high or low relative to the present, then it makes sense to wait until the uncertainty is resolved (Bachmann, Elstner and Sims, 2010). In other words, facing a more uncertain environment, firms pause hiring and investment, i.e. they “wait and see” how the future unfolds, which leads to a decrease in economic activity. As the future unfolds, there is pent-up demand for labour and capital. Firms are closer to their adjustment triggers in subsequent periods, leading to a rebound and even overshoot in economic activity, followed by a return to the steady state (Bachmann, Elstner and Sims, 2010). Thus, the initial “bust” is followed by a quick pick-up and overshoot in economic activity (Bachmann, Elstner and Sims, 2013). This provides a channel through which uncertainty shocks can exogenously influence economic activity.

Uncertainty can also negatively affect economic activity through risk aversion and risk premia. Greater uncertainty increases risk premia if investors are risk averse, by increasing the probability of default among lenders (expanding the size of the left-tail default outcomes) (Redl, 2015). This increase in borrowing costs can reduce growth, as emphasised in papers on the impact of uncertainty under financial constraints (summarised in Bloom, 2014, @Bachmann2013). Another mechanism related to risk premia is the confidence effect of uncertainty. In models where consumers have pessimistic beliefs, agents are so uncertain about the future they cannot form a probability distribution. Instead they have a range of possible outcomes and act as if the worst outcomes will occur, displaying a behaviour known as “ambiguity aversion.” As the range of possible outcomes (uncertainty) expands, the worst possible outcome becomes worse, so agents cut back on investment and hiring. In contrast, if agents are optimistic (they assume the best case), uncertainty can actually have a positive impact (Bloom, 2014).

Bloom (2014) also refers to two channels through which it can have a positive effect on economic activity. The “growth options” argument is based on the idea that uncertainty can encourage investment if it increases the size of the potential prize. This is due to the potential for an increase

[8] In the context of capital, these costs can have both a physical element (equipment may get damaged in installation and removal) and a financial element (the used-good discount on resale). In the context of labour, adjustment costs include recruitment, training, severance pay, as well as search frictions.

in upside gains, while the downside loss is limited to initial sunk costs, which leads to an increase in the expected profits from an investment. Thus, uncertainty creates call option effects (Redl, 2015).

The Oi-Hartman-Abel effect highlights the possibility that firms may be risk-loving if they can expand to exploit good outcomes and contract to insure against bad outcomes. For example, if a firm can easily halve production volumes in response to a price decrease, and double production if prices increase, it should desire a mean-preserving increase in uncertainty. This is because it receives 50% during bad outcomes and 200% during good outcomes. In effect, the firm is partly insured against bad outcomes by being able to contract and has the option to increase its advantage from good outcomes by expanding. However, for this mechanism to work, firms need to be able to expand or contract easily in response to good or bad news. Bloom (2014) argues that this effect is typically not very strong in the short run because of adjustment costs, but may be more powerful in the medium to long run.

The theoretical effects of uncertainty are therefore ambiguous, which is reflected in the empirical literature. Bonciani and Roye (2015) argues that in a general equilibrium framework the aforementioned effects may or may not be completely offset. In a New Keynesian Model, for instance, the monetary authority can partially offset the negative effects of uncertainty by reducing the nominal interest rate. They argue that this is the most important reason why many papers do not find a strong effect. However, when the monetary authority is constrained by the zero lower bound, or when there is imperfect pass-through, the effects of uncertainty become more significant, as the central bank cannot perfectly respond to the shock.

4.2 Empirical Findings

Recently there has been a surge in research interest in uncertainty. This has been driven by the idea that uncertainty increased during the financial crisis and its likely role in shaping the Great Recession. In addition, the availability of empirical proxies for uncertainty has increased, along with the ability to include uncertainty in a wide range of models (Bloom, 2014). There are two main challenges when it comes to empirical work on business uncertainty: how to construct proxies for uncertainty and how to distinguish a separate impact of uncertainty from recessions or periods of low confidence. Uncertainty entails a lack of knowledge regarding the set of possible outcomes and the probability of each occurring. It is unsurprising that there is no perfect measure of uncertainty, given its broad definition and the potential influence of such a broad range of factors.

The majority of studies have looked at macroeconomic uncertainty, using as proxies the implied or realised volatility in the stock market, GDP, bond yields or exchange rates. The rationale is that a more volatile series is more difficult to forecast, and is associated with a greater the degree of uncertainty (Bloom, 2014). A second group of proxies is derived from the dispersion of professional forecasts of economic variables. The rationale is that a larger dispersion of opinions about the future should indicate a higher degree of uncertainty. Other studies have constructed proxies based on references to "uncertainty" in the media, as well as the cross-sectional dispersion of firm-level productivity and profits (Girardi and Ruiter, 2015). Another type of indicator, which is used in this paper, is the dispersion of responses from business and consumer surveys and the dispersion of individual respondents' forecast errors. These survey-based measures have the advantage that they are derived from opinions of key economic agents, as opposed to outside observers (e.g. professional forecasters), or the choices of investors on financial markets, which may only partly reflect developments in the real economy (Girardi and Ruiter, 2015).

The evidence on the impact of uncertainty is limited because of the difficulty in isolating cause and effect. To identify the causal impact of uncertainty on firms and consumers, the literature has taken three approaches (Bloom, 2014). The first approach relies on timing, typically in a VAR framework, by estimating the movements in output, employment and investment that follow changes in uncertainty. A second approach uses structural models to quantify the potential effect of uncertainty shocks. A third approach exploits natural experiments like disasters, political coups, or exchange rate movements.

In a seminal paper, Bloom (2009) analysed the impact of uncertainty shocks in a structural framework. A structural model was used to simulate an uncertainty shock, producing the rapid drop and subsequent rebound in aggregate output and employment predicted by the "wait-and-see" effect. This simulated impact was compared to VAR estimations on actual data, using stock market volatility as a proxy for uncertainty. The results showed a good match in both magnitude and timing. A shock to uncertainty generated a decline and then an overshoot in both employment and production over a 6 month period.

Bachmann, Elstner and Sims (2010) used data from business surveys to investigate the relationship between uncertainty and economic activity within a structural vector autoregression (SVAR) framework. Based on business surveys for the US and Germany, they used the dispersion of survey responses, as well as the dispersion in individual forecast errors, as proxies for uncertainty. They found that innovations to these indicators had protracted negative effects on economic activity. The long-run effects of uncertainty shocks were similar to the long-run effects of negative confidence shocks. However, when uncertainty was restricted to have no long-run impact, which is what the "wait-and-see" effect would predict, uncertainty had no significant impact on activity. Consequently they argued that uncertainty could be seen as a symptom of poor economic times rather than a causal mechanism.

In a follow-up study, Bachmann, Elstner and Sims (2013) found that a shock to the survey-based measures of uncertainty was associated with a significant reduction in production and employment in both Germany and the US. German production declined and rebounded fairly quickly following an increase in uncertainty, broadly consistent with the predictions of the "wait-and-see" effect. However, only a modest fraction of output fluctuations was explained by movements in uncertainty. The response of US output to an uncertainty shock was persistent and prolonged, with limited evidence of a rebound. They argued that the difference in impact was unsurprising, because adjustment frictions were more important in Germany, where there are stronger labour market regulations. The results for the US data suggested that some of the other mechanisms proposed in the literature, such as financial frictions may be important.

Popescu and Smets (2010), for instance, argued that once a measure of financial stress is included in the regressions, the independent role of uncertainty shocks becomes minimal. They used a VAR framework, with forecaster dispersion as a proxy for uncertainty and credit spreads as a measure of financial stress. They found that real effects of financial stress were much larger and more persistent than the impact of uncertainty.

Leduc and Liu (2015) used traditional volatility measures, as well as survey-based measures of uncertainty to estimate its impact on output in a VAR framework. In their survey uncertainty could be measured directly as the fraction of respondents indicating uncertainty about the future as a factor limiting their spending plans (cars for consumers or capital expenditure for firms). They concluded that an uncertainty shock acted like an aggregate demand shock, raising unemployment and credit spreads, and lowering investment, inflation and short-term interest rates.

Baker, Bloom and Davis (2015) developed economic policy uncertainty indices for the US, based on the frequency of references to policy uncertainty in newspapers, the number of tax code provisions about to expire, and the disagreement among forecasters over future government purchases and inflation. Using VARs they found a large negative real impact on employment and industrial production. The results were similar to Bloom (2009), except for the positive rebound. An increase in their uncertainty proxy of the size seen during the financial crisis was associated with a loss of around 2 million jobs and a decline in industrial production of 2.5% for the US.

Baker and Bloom (2013) used cross-country panel data on stock market levels and volatility as proxies for the first and second moments of business conditions (i.e. confidence and uncertainty). They then used natural disasters, terrorist attacks and unexpected political shocks as instruments for the stock market proxies. They found that both variables were highly significant in explaining GDP growth, with uncertainty shocks accounting for at least a half of the variation in growth.

Binding and Dibiasi (2015) showed how different uncertainty indicators reacted to the unexpected policy change, when the Swiss National Bank decided to return to a floating exchange rate regime in 2015. The impact of this exogenous increase in uncertainty on the investment plans of Swiss firms was examined, using firm-level investment surveys and a difference-in-difference framework. Firms affected by uncertainty decreased their planned investment (into equipment/machinery and construction), relative to firms which were not affected. However, once they controlled for the degree of irreversibility of firm investment, the relationships were no longer significant.

Jurado, Ludvigson and Ng (2015) argued that indicators of uncertainty should reflect the common variation across many series, and that the forecastable component of each series should be removed when calculating volatility. They constructed new indicators using a large dataset of macroeconomic and financial indicators, as well as firm-level data. Increases in the volatility of forecast errors were interpreted as increases in uncertainty. Their estimates implied that quantitatively important uncertainty episodes occurred more infrequently than indicated by common uncertainty proxies. However, when they did occur, they displayed larger and more persistent correlations with real activity. Using multivariable VARs, they found that large positive shocks to uncertainty led to sizable and protracted declines in real activity, but did not exhibit the overshooting pattern found in other studies.

4.2.1 Evidence for South Africa

There is little evidence on the impact of uncertainty in developing countries, where uncertainty is typically higher by about one-third than in developed countries (Bloom, 2014). This may be because developing countries tend to have less-diversified economies, which are more exposed to output and price fluctuations of volatile goods such as commodities. Developing countries appear to have more domestic political shocks, are more susceptible to natural disasters, and often have less-effective fiscal and monetary stabilisation policies. It is possible that fluctuations in uncertainty are important drivers of business cycles in developing countries, given that they experience higher levels of uncertainty.

Redl (2015) argued that investigating uncertainty in developing countries could help to disentangle the effects of financial shocks from uncertainty shocks. During the Great Recession many developing countries experienced increases in uncertainty, as their trading partners entered recessionary periods. Yet they did not experience the same levels of financial stress and instability as developed countries. He constructed an index of uncertainty for South Africa, based on disagreement among professional forecasters, the number of newspaper articles discussing economic uncertainty in South Africa, and references to uncertainty in the SARB's Quarterly Review. The index showed high levels of uncertainty around the period of democratic transition in the early 1990s, the large depreciation of the currency in 2001 as well as the financial crisis of 2008. Using an SVAR framework, the results showed that uncertainty was a leading indicator of recessions in South Africa. An unanticipated increase in uncertainty was associated with a future decrease in output, employment, asset prices and investment. The results were also robust to the inclusion of consumer confidence and credit spreads as a measure of financial stress, although the sizes of the effects were moderated.

McClean (2015) constructed a news-based index for aggregate South African policy uncertainty. He found moderate evidence of a correlation between this index and the SAVI index, and a modest but theoretically and empirically consistent relationship with SA government bond yields.

Hart (2015) investigated the relationship between sentiment and economy activity in South Africa. The BER's survey of the manufacturing sector was used to construct measures of uncertainty and confidence, as well as trends in production, employment and investment. A VAR framework was used to estimate the impact of uncertainty and confidence shocks on production, investment and employment within the South African manufacturing sector. None of the uncertainty measures were found to be significant, probably due to the small sample size. The study was closely based on Bachmann, Elstner and Sims (2010), which also measured uncertainty in a manufacturing sector using micro-level business survey data. This paper will build on this approach, expanding the study to include all of the surveyed sectors for the full available sample period.

The literature provides suggestive but not conclusive evidence on the impact of uncertainty on economic activity. It is not yet clear whether uncertainty in itself has an impact on the business cycle or whether it is an epiphenomenon that occurs during recessions or periods of low confidence. Hence there is a need to further examine the effect of uncertainty on the real economy. This is particularly true for developing countries, where uncertainty is generally higher. The following section describes the BER business tendency surveys that are used to construct the measures of sentiment for South Africa.

5 Data: Business Tendency Surveys

Business tendency surveys are conducted to obtain qualitative information that is useful in monitoring the current business situation and forecasting short-term developments in the business cycle. Qualitative surveys can often be completed more easily and quickly than traditional quantitative surveys, which means that the results can be published much sooner. The information is therefore more current than official statistics, which are often released with a significant delay by statistical agencies (OECD, 2003).

Business tendency surveys have traditionally been used by respondents as a gauge of sectoral business conditions. Series derived from business surveys are increasingly employed by economic analysts, due to the prompt availability of the data, and because some of the indicators derived from business surveys have proved to be useful for monitoring and forecasting the business cycle. The survey information has the advantage of focusing on the assessments and expectations of economic developments by relevant economic decision-makers. Variables related to expectations may reflect cyclical changes earlier than corresponding quantitative statistical series (i.e. expectations lead to plans that are then implemented and will then be picked up in quantitative statistics). This is reflected in the extensive use of confidence indicators as leading and coincident indicators of the business cycle (OECD, 2003).

5.1 The BER Business Tendency Surveys

The BER, a research institute attached to Stellenbosch University, has been conducting business tendency surveys in South Africa since March 1954. The BER's quarterly business surveys are similar to the business tendency surveys conducted all over the world, including the German Ifo Business Climate Survey, the Federal Reserve Bank of Philadelphia's Business Outlook Survey, the European Commission business survey, and the Tankan survey conducted by the Bank of Japan.

The questions are qualitative in nature and aim to provide information on developments in each sector since the last release of official figures. For the most part the survey answers fall into three categories: "up", "the same" or "down". The questions have remained largely unchanged since inception and most of the responses can be tracked over time.

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 building and trade sectors (i.e. retail, wholesale and motor vehicles). The questionnaires are completed by senior executives of the firms. 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.

Panels are useful for conducting business tendency surveys, as changes in the survey results are more likely to reflect changes in the actual variables of interest over time, rather than changes in the sample from the one survey to the next (especially if no post stratification is done to provide for changes in response patterns). A core group ensures that the results remain comparable between surveys, as it reflects the views of the same respondents over time. The survey results reflect changes in the variables under consideration and are less influenced by the participation or non-participation of particular firms. This is especially useful if little is known about the composition of the universe (Kershoff, 2002).

In accordance with the international norm, stratified deliberate sampling is used to design the BER's survey panels. Participants are selected to be representative of particular sectors, regions and firm sizes. The list of participants is reviewed every few years to ensure reasonable representation of the population universe (Kershoff, 2000). The exact number of firms in the universe is unknown to the BER as censuses of the business sector in South Africa are not conducted regularly (Kershoff, 2002).

Panel sizes and response rates determine the representativeness of the sample. Panels have to consist of a certain minimum number of participants in order to be regarded as fair representations of the universe. The minimum size depends on the size of the universe and the level of aggregation (Kershoff, 2002). Figure 1 illustrates the number of respondents over time per sector. The sample runs from 1992Q1 to 2015Q3, although the survey of the services sector only started in 2005. Around 1,000 completed questionnaires were received every quarter, leading to an overall sample size of 106,274. The overall panel sizes and response rates have remained relatively stable over time, although they are relatively low by international standards (Kershoff, 2015).

Kershoff (2002) found that the BER's trade and building panels were fair reflections of the universe, taking response rates into account and comparing the composition of the survey panels with census and other official data. However, the number of participants per sector was too low to consider subsectors as sub-panels. Thus, the degree of representation was adequate to validate the overall results, but the responses per subsector and per province should be interpreted with caution. The survey responses are therefore not disaggregated further into subsectors below.[9]

[9] We could include some more descriptive statistics here, such as the panel sizes and response rates for the various

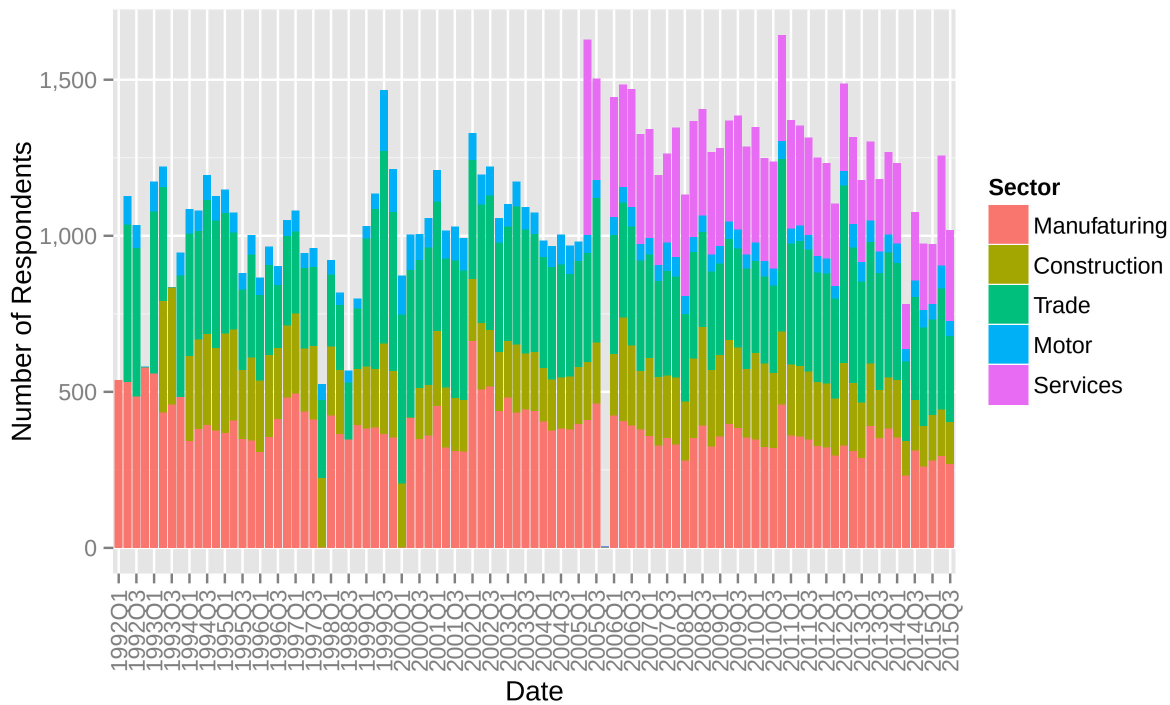

Figure 1: The number of respondents over time per sector

Unfortunately, conventional statistical measures cannot be calculated to measure the representativeness of non-probability samples. Kershoff (2015) argued that the BER's sampling errors (which arise when information is obtained from a sample instead of the entire population) are probably larger than usual, because it does not use random sampling, employs a panel, has a relatively low response rate and, in the case of some subsectors has less than the ideal minimum number of completed responses. However, the representativeness of sampling units has a substantially smaller impact on qualitative survey results than quantitative surveys. In the case of a qualitative surveys, the purpose of the research is to establish the majority view of the direction of change of a particular activity, rather than the quantitative size of the change. The majority view is taken as an indication of the direction and intensity of the trend of the activity in question. As the majority of firms usually share the same experience, a slightly unrepresentative panel will likely produce similar results as a fully representative one (Kershoff, 2002).

The OECD (2003) notes that there is considerable practical experience which shows that for business tendency surveys non-random samples can give acceptable results. Business survey results tend to remain valid even if the sample size is small and response rate is relatively low. According to the OECD (2003), a rule of thumb is that around 30 reporting units is sufficient to obtain an acceptable level of precision for each strata. In practice this is a maximum because some kinds of activity will be dominated by a few very large enterprises. The reason is that the required sample size depends mainly on the variance of the responses. Changes in results between consecutive surveys based on a stable panel sample have smaller variance than results derived from completely independent surveys and the variance of ordinal-scaled data is usually significantly lower than that of quantitative data. The sample sizes illustrated in Figure 1 therefore seem adequate to uncover trends in the data.

surveys over time? For instance, we could plot the response rates by sector?

In the case of most qualitative surveys, no provision is made for firms that were not selected or did not respond during sampling, as it is implicitly assumed that their performance corresponds with those of the participants. This corresponds to the OECD (2003) suggestion of the "missing at random" assumption, which assumes the non-participating or non-responding firms have the same distribution as the responding firms for the period. Kershoff (2015) argues that this is a reasonable assumption, given that the same factors impact on firms in the same sector (they tend to follow the same trend) and the responses cannot vary infinitely (as is the case with a quantitative survey), but are limited to "up", "the same" or "down". He found evidence for this assumption when the inclusion of the latecomers had almost no effect on the volatility and tracking record (i.e. the correlation between the survey data and the corresponding quantitative series) of the survey results, even at higher levels of disaggregation.[10]

5.2 The RMB/BER Business Confidence Indicator

The survey results of successive quarters provide a means of tracking cyclical movements, pinpointing trend changes and making forecasts (Kershoff, 2000). The BER constructs a successful business confidence indicator from the survey responses. It is widely accepted as an accurate leading indicator for the South African business cycle and is used by the SARB as a component of the official composite leading indicator series.

In constructing the business confidence indicator the most important issues are which questions to use and the weightings applied to the responses. The business survey contains questions, amongst others, on current and expected future developments regarding sales, orders, employment, inventories, prices and constraints, all of which have an impact on business confidence. To form a composite confidence indicator these responses would need to be weighted.

The BER business confidence index is constructed from a specific question that appears in all of the surveys (Q1): *"Are prevailing business conditions: Satisfactory, Unsatisfactory?"* The business confidence index reflects the weighted percentage of respondents that rated prevailing business conditions as *"Satisfactory"* in a particular sector. The BER measures business confidence on a scale of 0 to 100, where 0 indicates an extreme lack of confidence, 50 neutrality, and 100 extreme confidence. The business confidence index reveals a rating of business conditions at a particular point in time and respondents do not have to compare the current situation with that of a year ago. The indicator therefore reflects confidence in current conditions (activity) rather than forward-looking confidence.

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 consideration when rating prevailing business conditions, which solves the problem of weighting different factors correctly (Kershoff, 2000).

In line with the international best practice, all the survey responses are weighted (except for the building survey results). 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

[10] The BER does not adjust individual weights to provide for changes in the response pattern. No calibration or any other form of post-stratification is carried out to correct the estimated value (when the sample is not an accurate reflection of the population, or the response pattern changes between quarters). Missing items (specific questions) and missing responses (questionnaires) are not imputed. The results are not revised to provide for questionnaires received after the results have been processed (Kershoff 2015).

subsectors). Each firm gets a weighting in relation to turnover or size of workforce (in the case of manufacturing) to provide for widely differing sizes.[11] The subsector size weight is based on the composition of production or sales for each subsector, as calculated by Stats SA. The BER does not apply sample weights, as it does not have access to the National Business Register and cannot calculate selection probabilities.[12] Thus, responses are weighted by firm size and sector weights to obtain the sectoral results.

The BER business confidence index is calculated as the unweighted mean of five sectoral indices: manufacturing, building contractors (other building subsectors are disregarded), retailers, wholesalers and new vehicle dealers (used vehicles and spare parts are disregarded). Naturally, there are other ways to aggregate the indicators, but practical experience has shown that the balances are not very sensitive to the choice of weighting, and in practice it is often sufficient to use a single variable in weighting all the survey answers [OECD2003]. Indeed, as discussed in detail below, in this case the specific weighting turns out to have very little impact on the confidence indices. For many of the indicators, the weighted and unweighted versions are almost indistinguishable, which suggests that the specific weighting adopted does not significantly alter the results.

This confirms the results found by Kershoff (2015),[13] who tested alternative methods of aggregation to calculate the confidence indicator: a different allocation of firm size weights; the introduction of dynamic individual weights (post-stratification) to provide for changes in the response pattern between consecutive surveys (to handle non-responses); the application of the OECD's recommended two-step weighting procedure; the inclusion of latecomers to increase the number of responses; the use of different sector size weights for the export variables; and the combination of a number of subsectors to produce a higher level of aggregation. The preliminary findings showed that the results were not sensitive to the number and weights of respondents.

The BER business confidence index has proved useful both as an indicator of economic growth and as a good leading indicator of the South African business cycle. It is used as one of twelve leading indicator series by the SARB do date official turning points in the business cycle. Laubscher (2014) also found that it can provide good 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).

6 Indicators of Sentiment

This section uses the BER business tendency surveys and the methodology suggested by Bachmann, Elstner and Sims (2010) and Bachmann, Elstner and Sims (2013) to calculate indicators of business sentiment in South Africa. Micro-data for the manufacturing, building, trade and services sectors

[11]Size weights are used in processing qualitative answers because the economic significance of the replies from different firms is linked to the size of the firm - the larger the enterprise the more important the response. Unlike quantitative surveys, where weighting is usually inherent in the variables, weighting is necessary for qualitative surveys, because the variables typically collected do not inherently represent the size of a business (INIS 2014). In this case a logarithmic function is used to determine weighting factors for nine size ranges, similar to the Ifo survey.

[12]The BER does not apply sample weights (i.e. the inverse of the probability with which each reporting unit has been selected). This is akin to assuming that the probability of selection is the same for all units (the weights are therefore identical), which would be the case if firms where selected on a simple random basis, e.g. without stratifying the target universe into large and small units (OECD 2003). I would guess that large firms respond with greater probability because they are more interested in the survey results. So this could potentially bias our estimates.

[13]George's (2015) paper says "Do not quote", so we might have to remove these references.

were obtained from the BER. This allows for the calculation of proxies for confidence and uncertainty. The data runs from the early 1990s for most of the sectors, and from 2005 for the services sector.

6.1 Confidence

There are a number of other questions on the BER business surveys which have the potential to provide insight into the role of sentiment in South African economic activity. Following the international literature, a distinction is made between indicators of confidence for current conditions and for forward-looking conditions. For consistency, confidence measures are derived from the same questions that are present in all of the sectoral business surveys.

Two questions focused on current developments are used to construct confidence measures for current general business conditions: the first is the question used by the BER to construct their business confidence index (Q1): *"Are prevailing business conditions: Satisfactory, Unsatisfactory?"* In effect this confidence indicator recreates the BER confidence index, but with latecomers included and amended weightings. The second indicator is based on the question (Q2A): *"[Estimated development in current quarter] Compared with the same quarter of a year ago, are General Business Conditions: Better, the Same, or Poorer?"*[14]

The forward-looking confidence indicators are derived from the question (Q2P): *"[Estimated development in next quarter] Compared with the same quarter of a year ago, will General Business Conditions be: Better, the Same, or Poorer?"* In other words, it asks whether general business conditions in time $t+1$ will be better, the same, or poorer, compared to $t-3$?[15]

Respondents use the same quarter in the previous year as the reference period, whereas other surveys often use the previous period for comparison. Responses are relative to levels in the same quarter of the previous year, which is equivalent to the year-on-year growth rate in each quarter. The cyclical profiles are therefore easier to detect because they contain no trend and are usually considered as a growth cycle or growth rate cycle (OECD, 2003). It also implies that seasonal adjustment is not required.[16]

Many institutions calculate confidence measures based on a set of survey variables. These composite indicators may achieve a better trade-off between responsiveness and stability. Composite indicators can be constructed to have fewer false alarms and fewer missed turning points than individual components and tend to have more stable lead-times. They also have the capacity to react to various sources of economic fluctuations, while being resilient to fluctuations affecting single components (ECB, 2013). The European Commission builds composite indicators by aggregating the survey responses from combinations of questions for five sectors. For instance, the industrial indicator is an average of the balances of questions relating to production expectations, order books and stocks of finished goods (with an inverted sign), while the retail trade indicator is an average of the balances

[14] Hart (2015) argues that the success of the BER's confidence index as a leading indicator is due to current conditions influencing expectations for the future. But it is not clear to me why a question on current conditions (i.e. activity) would be a leading indicator and not a coincident indicator? Perhaps it is because agents take expectations of the future into account when answering this question, which the current period's official statistics do not?

[15] The Manufacturing survey has an additional question on future general business conditions: *"In comparison to current levels in your sector, what do you expect the general business conditions to be in 12 months' time: Higher, Same, Lower?"* This is the question used in Hart (2015), but it is only asked in the Manufacturing survey.

[16] A common difficulty is that respondents may not actually use the reference period specified in the questionnaire in answering the question (OECD 2003). It is possible that this is the case in the BER survey responses. For example, answers to the forward-looking questions may compare the next quarter t+1 to period t, instead of period t-3.

to questions relating to present and future business situation and stocks (with an inverted sign) (OECD, 2003).[17]

However, as mentioned above, the BER regards the use of one question to measure confidence as an advantage, because respondents will take a wide variety of factors into consideration when rating general business conditions. This removes the problem of which questions to aggregate and which weights attach to the various potential questions. The OECD (2003) also argues that answers to questions on the general business situation will usually be based on a combination of factors, such as the respondents' appraisals about order books and expected new orders, as well as expectations about interest rates, exchange rates and political developments.[18]

As discussed above, confidence indicators are almost always based on the balance statistics. Individual answers are aggregated by subtracting the share of negative answers from the share of positive answers. This presents a single figure as a summary of responses to each question (Santero and Westerlund, 1996). The BER converts almost all the responses to net balances, i.e. the weighted percentage of respondents indicating that a particular activity is "up" less the weighted percentage indicating "down". It is the cross sectional average of the survey responses if the standard quantification method for survey data is used, whereby the "up" category is quantified by +1, "the same" category by 0 and the "down" category by -1.

For each of the surveyed sectors, confidence measures of current conditions (activity measures) and forward-looking conditions are calculated. For each sector the responses are weighted by firm size and subsector weight, and balances are calculated. Thus, confidence reflecting current conditions may be defined as: $CC.Confidence_t = Frac_t(Up) - Frac_t(Down)$. Forward-looking confidence relate to firms' expectations concerning future business conditions: $FL.Confidence_t = Frac_{t+1}(Up) - Frac_{t+1}(Down)$. Following the advice from the INIS (2014), the sectoral indicators are then weighted by GDP share to form the overall aggregate indicators of business confidence.[19]

Figure 2 compares the RMB/BER Business Confidence Index to the confidence indicator derived from the same question on current conditions. The first confidence (or activity) indicator and the published confidence index are very similar, even though the BER uses a slightly ad hoc weighting procedure. The difference is probably due to altered weightings and the BER's exclusion of latecomers. The indicators for the respective sectors based on this question, not illustrated here, are also very similar to the published sector confidence indices.

Figure 3 and Figure 4 compare the aggregate weighted and unweighted versions of two of the confidence indicators: the first activity indicator and the forward-looking indicator. The unweighted versions are calculated by stacking all of the available responses from all of the surveys, and are therefore completely unweighted. In both cases they are very similar, with the weighted versions slightly more volatile than the unweighted indicators. Thus, the specific weighting turns out to have very little impact on the confidence indices. This should give us confidence that the specific

[17] We could easily make similar composite indicators? For instance, we could combine the balances for the questions on production volumes, order, etc. Otherwise, we could just exclude this reference.

[18] Bachmann et al (2010) and Hart (2015) also construct 4 measures of activity from the survey data: production, investment and employment and employment turnover. The questions on investment are not present in all of the surveys. But I have calculated the measures of production, employment, and employment turnover (which just adds the fractions of respondents indicating "up" and "down". It is not yet clear if these will be useful, as we have official statistics on production and employment.

[19] Should I combine responses to new cars, used cars and spare parts for motor trade, or just use new vehicles as the BER does? Where can I get Motor vehicles GDP shares? At the moment I just assume they are 5% of the trade sector.

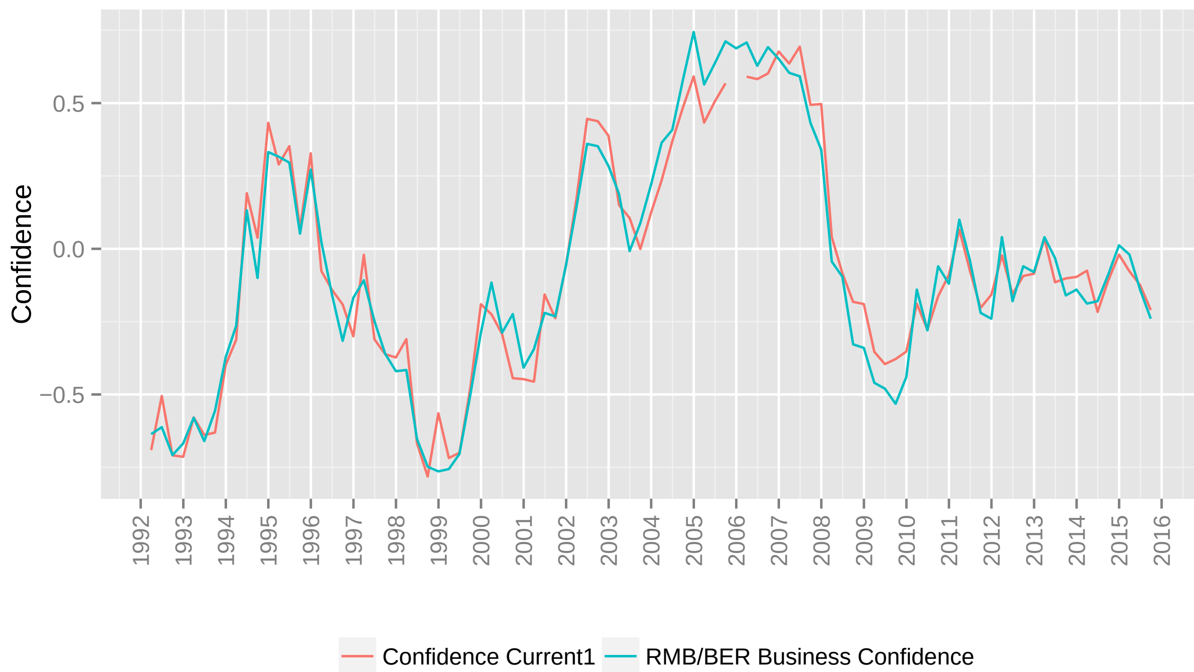

Figure 2: Weighted Confidence compared to the RMB/BER Confidence Index

weighting adopted does not significantly alter the results. The same is true of the respective sector indices, not illustrated here.

Figure 5 illustrates the two unweighted aggregate confidence indicators for current conditions, as well as the aggregate forward-looking confidence index.[20] The shaded areas denote the recessionary periods according to the official turning points provided by the SARB. The indices follow a similar cyclical trend over the business cycle and are very highly correlated. They seem to match up closely to the different phases of the business cycle and appear to be useful as leading or coincident indicators. The forward-looking index seems to lead the two current conditions indices to some extent. The same is true of the respective sectoral indicators, even though their trends are slightly different (and they have some missing quarters). The two indicators generated from the question on general business conditions do not increase as substantially as the other indicator (derived from the BER question) over the protracted upswing phase from around 2003 to 2007, which is a feature of all of the respective sectoral indicators. Nevertheless, these survey-based measures appear to be plausible and potentially useful indicators of business confidence in South Africa.

[20]We could also take the geometric mean of the indices and then normalise it to the average of the base year, as the Ifo does? I also generated the indicators from firm-specific questions on production, instead of the question on general business conditions. As found in the literature, the indicators generated from the more firm-specific questions are very highly correlated to the indicators for general business conditions. Previous studies have concluded that answers on general business conditions are essentially indicators of firm-specific business conditions.

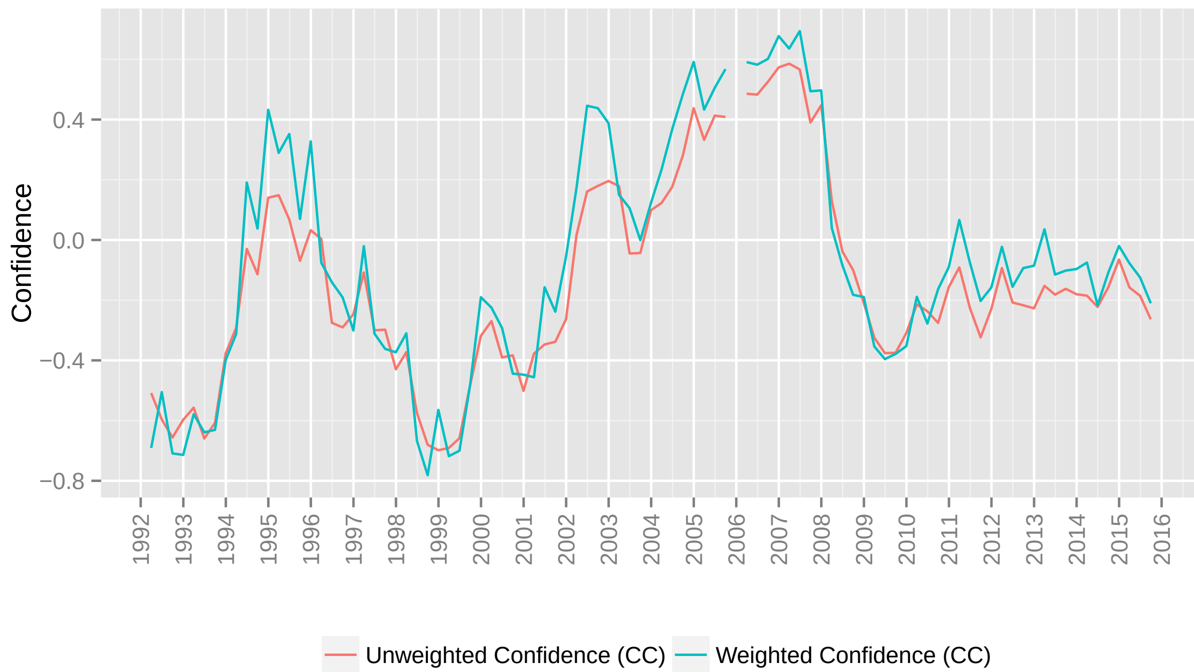

Figure 3: Weighted and Unweighted Confidence - Current Conditions

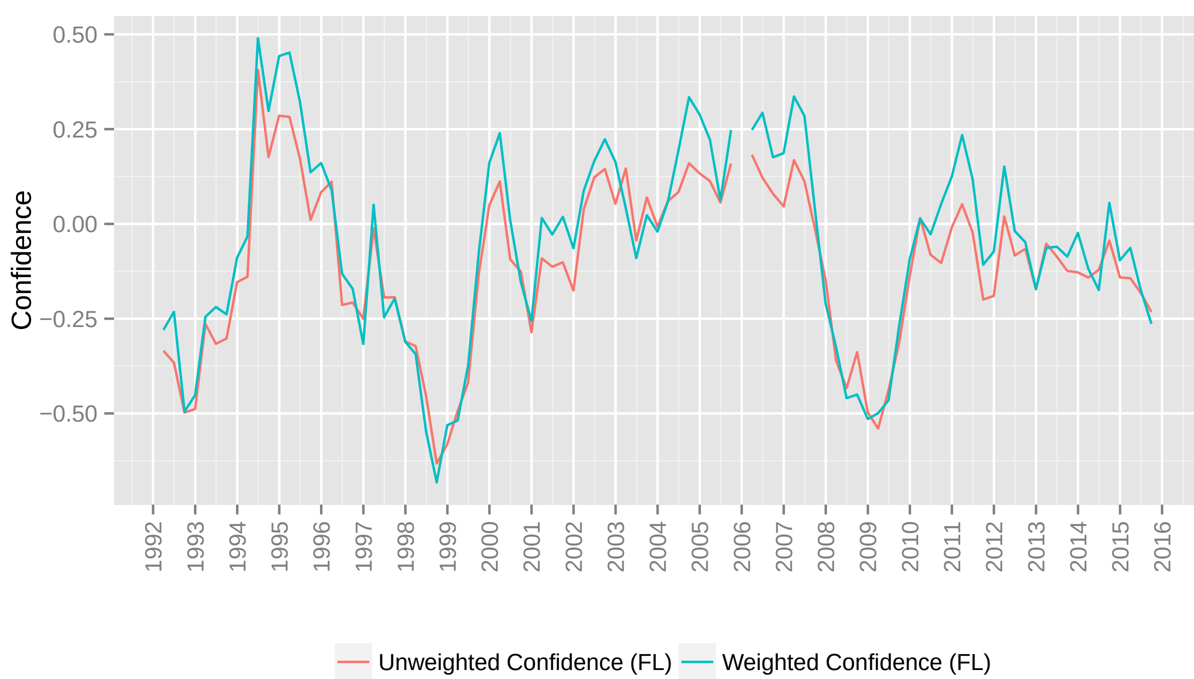

Figure 4: Weighted and Unweighted Confidence - Forward-looking

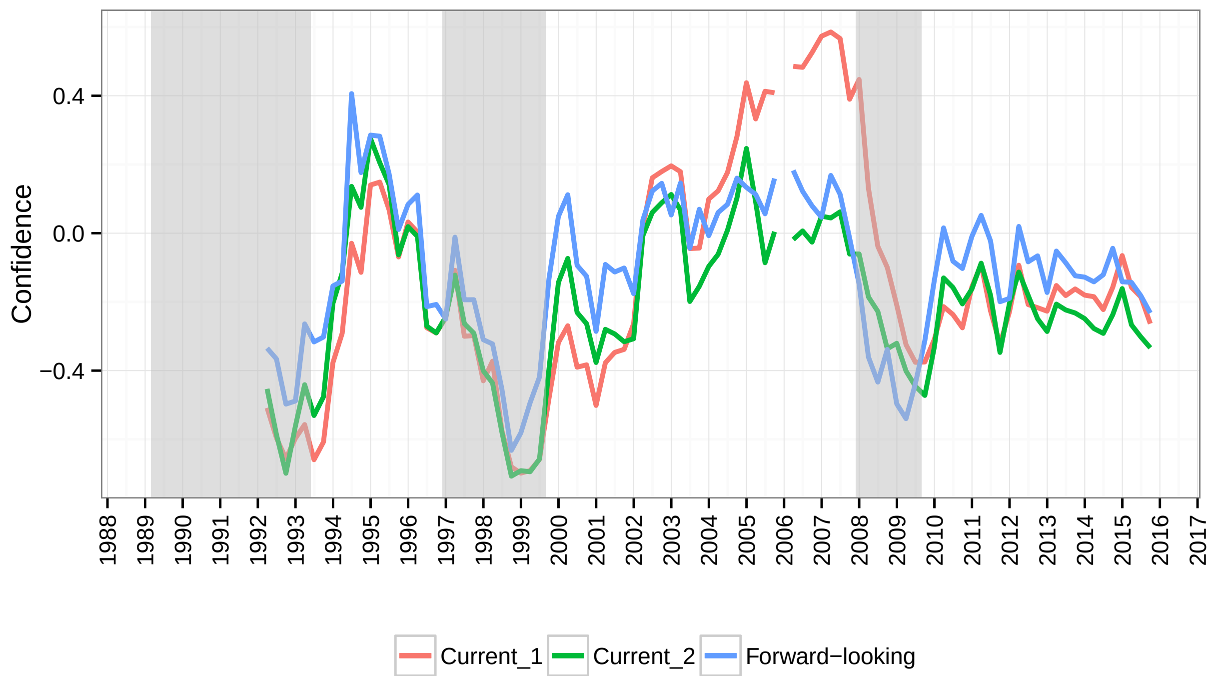

Figure 5: Unweighted Confidence Indicators

6.2 Uncertainty

This section follows Bachmann, Elstner and Sims (2010) and Bachmann, Elstner and Sims (2013) by calculating two measures of uncertainty: the cross-sectional dispersion of forward-looking responses and the cross-sectional dispersion in individual firm's expectation errors. The micro-data allows the calculation of *ex ante* disagreement and *ex post* forecast error variance. These measures both capture a low level of predictability. The cross-sectional dispersion method can be seen as akin to the forecaster disagreement measure used to proxy macro uncertainty by Baker and Bloom (2013).

The first measure of uncertainty is the cross-sectional dispersion of forward-looking responses, using the same question as before (Q2P): *"[Estimated development in next quarter] Compared with the same quarter of a year ago, will General Business Conditions be: Better, the Same, or Poorer?"* The uncertainty measures are the cross-sectional standard deviation of responses:

$$U_t = \sqrt{(Frac_t(Up) + Frac_t(Down) - [Frac_t(Up) - Frac_t(Down)]^2)}$$

Frac(Up) is again defined as the weighted fraction of firms in the cross section responding with "Better" at time t. The weightings are applied in the same way as for the confidence indicators, i.e. firm size and subsector weights. The sectoral indicators are then aggregated again with GDP shares as weights.

Figure 6 illustrates the centred[21] weighted and unweighted uncertainty indicators, based on *ex ante* disagreement in forward-looking responses. As was the case for the confidence indicators, the unweighted versions are calculated by stacking all of the available responses from all of the

[21] I normalised/standardised them for easier and clearer graphical presentation.

surveys. Again, the weighted and unweighted versions are similar, with the weighted indicator slightly more volatile. However, there are two substantial differences between the two measures. The weighted index exhibits a large trough in 2004, not mirrored by the unweighted index, while the unweighted index has a larger dip and subsequent recovery around the financial crisis in 2008. The sectoral uncertainty indicators (not illustrated here) exhibit similar trends, although there are some idiosyncratic spikes and troughs.

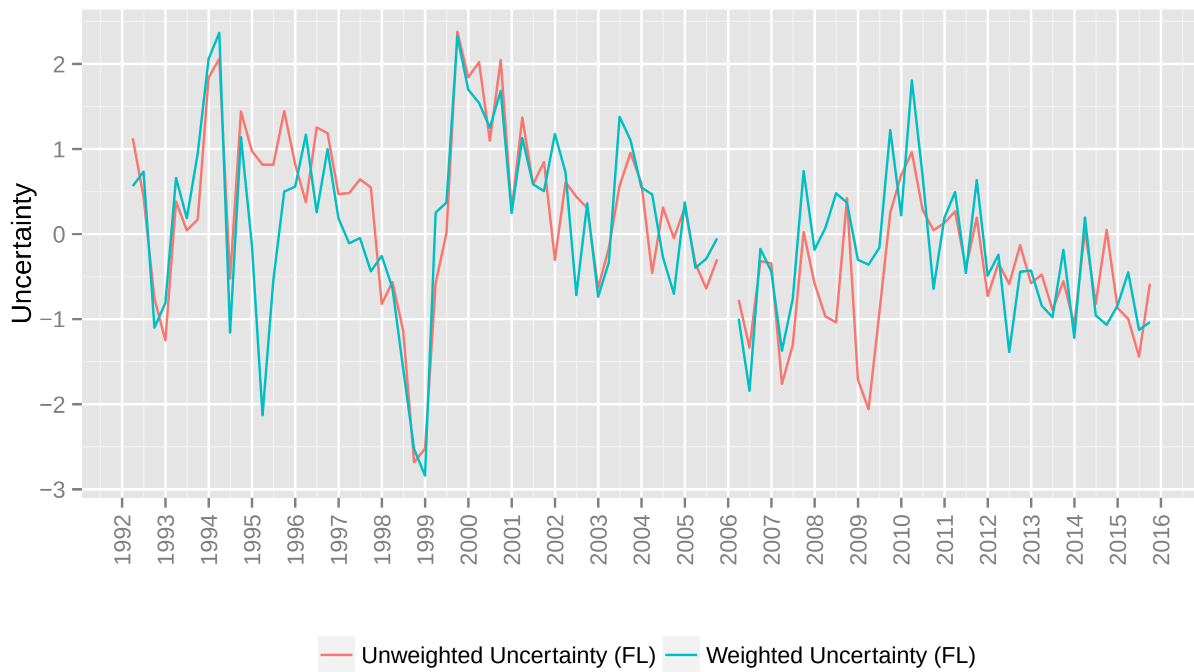

Figure 6: Uncertainty from forward-looking dispersion: Unweighted and Weighted

Bachmann, Elstner and Sims (2010) and Bachmann, Elstner and Sims (2013) noted that there are two potential problems with this proxy. First, time-varying cross-sectional dispersion in survey responses might simply be due to different firms reacting differently to aggregate shocks, even with constant uncertainty.[22] Second, time variation in the dispersion of expectations might simply reflect time variation in the heterogeneity of expectations, without the degree of subjective uncertainty changing over time. Accordingly, they recommended a qualitative index of the *ex post* forecast error standard deviation, which requires access to the micro-data. Forecast error is the error in individual firm's expectations, which excludes heterogeneous but certain disagreement in expectations.

The panel dimension of the survey is exploited to construct qualitative measures of *ex post* forecast errors. The same question is used to construct the uncertainty indicator (Q2A): *"[Estimated development in current quarter] Compared with the same quarter of a year ago, are General Business Conditions: Better, the Same, or Poorer?"*[23] Thus, the survey in period t is used to extract the

[22] They do a variance decomposition of uncertainty and compare the "within" and "between" variance at a subsector level. The idea is that a difference in factor loadings for aggregate shocks might be due to industry-specific adjustment and production technologies. They argue that the high "within" variance and the low "between" variance, means that time series movements in dispersion are not explained by manufacturing subsectors getting more or less different over the business cycle. We could do this as well, but I am not quite sure how it works?

[23] I have also calculated uncertainty indicators based on the BER question and indicators for production uncertainty.

Table 1: Possible Expectation Errors

		$Q2A_{t+1}$		
		Better	Same	Poorer
	E(Better)	0	-1	-2
$Q2P_t$	E(Same)	1	0	-1
	E(Poorer)	2	1	0

expectations of general business conditions in time $t+1$ relative to $t-3$. The errors are then calculated by subtracting these expectations from the actual realisations from the survey at time $t+1$, relative to $t-3$. For example, for a firm that expected an improvement in (i.e. better) conditions, the realisation of better conditions would be coded as a 0 forecast error, no change would be coded as a -1 forecast error, and poorer conditions would be coded as a -2 forecast error. Table 1 illustrates the 9 possible expectation errors that arise.[24]

Uncertainty was then measured as the cross-sectional standard deviation of the expectation errors in each quarter: $U_t = STD(Error_{t+1})$. Although it is based on the realised expectation errors in the next quarter, this is dependent on the knowledge and level of uncertainty in the current period. Thus, the standard deviation of realised expectation errors at time $t+1$ constitutes uncertainty in t (Bachmann, Elstner and Sims, 2010). This timing does not require decision-makers to know anything about the future, other than that it is more or less uncertain.

Figure 7 illustrates the centred weighted and unweighted uncertainty indicators, based on the *ex post* dispersion in expectations errors. The weighted and unweighted versions are similar, with the weighted indicator slightly more volatile. Again, the unweighted index has a larger dip and subsequent recovery around the financial crisis in 2008. The sectoral uncertainty indicators (not illustrated here), exhibit similar trends, although there are a few idiosyncratic spikes and troughs.

Table 2 shows that the correlations between these measures of uncertainty are all significant, which supports the findings in Bachmann, Elstner and Sims (2010) and Bachmann, Elstner and Sims (2013). The correlations between the forward-looking dispersion measures and the expectations error measures are 0.55 and 0.4 for the unweighted and weighted versions. The fact that both conceptually different proxies for uncertainty are reasonably similar lends some support to the widespread practice of proxying uncertainty with survey disagreement (Bachmann, Elstner and Sims, 2010). If the dispersion series were mainly driven by heterogeneous but certain disagreement then one would expect *ex ante* dispersion to be only weakly correlated with the *ex post* forecast error standard deviation (Bachmann, Elstner and Sims, 2013).[25]

Figure 8 compares the two unweighted uncertainty indicators, with the shaded areas again representing recessionary periods in South Africa. The indicators exhibit similar cyclical patterns over the

There are duplicated id pairs in the surveys - which is a mistake - so I exclude them. Should we impute missing sectoral values with aggregated data, and should we interpolate the 2005Q4 missing values?

[24] Again, a common difficulty is that respondents may not actually use the reference period specified in the questionnaire in answering the question (OECD 2003). It is possible that this is the case in the BER survey responses. For example, answers to the forward-looking questions may compare the next quarter t+1 to period t, instead of to period t-3. Kershoff (2015) admits this possibility and offers it as one explanation for potential seasonal patterns in the data. We can try alternatives like the average of previous changes in the activity variable?

[25] Bachmann et al (2013) construct another proxy for uncertainty based on these forecast errors. It is a measure of the average size of idiosyncratic forecast errors, which one would expect to be larger in a more uncertain environment. We could also do that? Another extension would be based on the work of Girardi et al (2015), where they extend the dispersion measure to include all 22 forward-looking questions in the EU survey. We can also investigate whether these measures are correlated with other proxies.

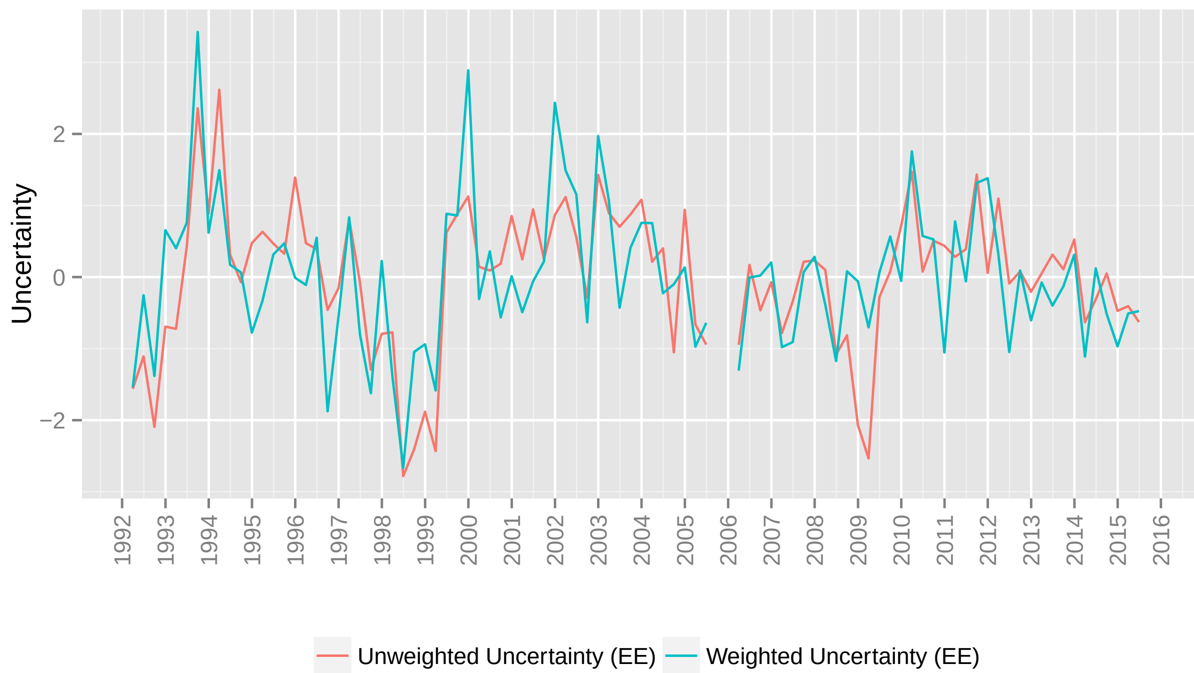

Figure 7: Uncertainty from Expectation Error dispersion: Unweighted and Weighted

Table 2: Correlations in Uncertainty Indicators

	Unw_FL	Unw_EE	Weighted_FL
Unw_FL			
Unw_EE	0.55***		
Weighted_FL	0.77***	0.47***	
Weighted_EE	0.29***	0.72***	0.40***

business cycle. They point to three troughs in uncertainty around 1993, 1999 and 2009, all of which were followed by large increases. The three troughs occurred towards the end of the three official downswing phases in the business cycle over the period. Uncertainty then spiked around the lower turning points (i.e. troughs) in output. The first episode coincides with the recessionary period around South Africa's Democratic transition. The second spike is associated with the recession following the Asian crisis, and financial distress associated with Russia's default on its sovereign debt and the collapse of Long Term Capital Management. The third episode is related to the financial crisis and the subsequent Great Recession.[26] Interestingly, the increase in uncertainty around the financial crisis in 2008, particularly for the weighted measures, is not as pronounced as has been found for many developed countries (e.g. Bachmann, Elstner and Sims, 2013; Bloom, 2014).

[26]In addition, there seems to be some increases around 2002-2003, which corresponds to the period when some South African business cycle indicators signalled a potential turning point. This was ultimately not considered an official reference turning point by the SARB, because the criteria in terms of amplitude and duration were not met. There are a few smaller spikes in 1996, 2003 and at the end of 2011. According to Redl (2015), 1996 may relate to EU/South African free trade area talks, the new Constitution and political unrest; 2003 may be related to the stagflation induced by the large and persistent exchange rate depreciation (of 50%); 2011 may be related to the Eurozone crisis, chicanery around raising the US federal debt ceiling, and the earthquake in Japan.

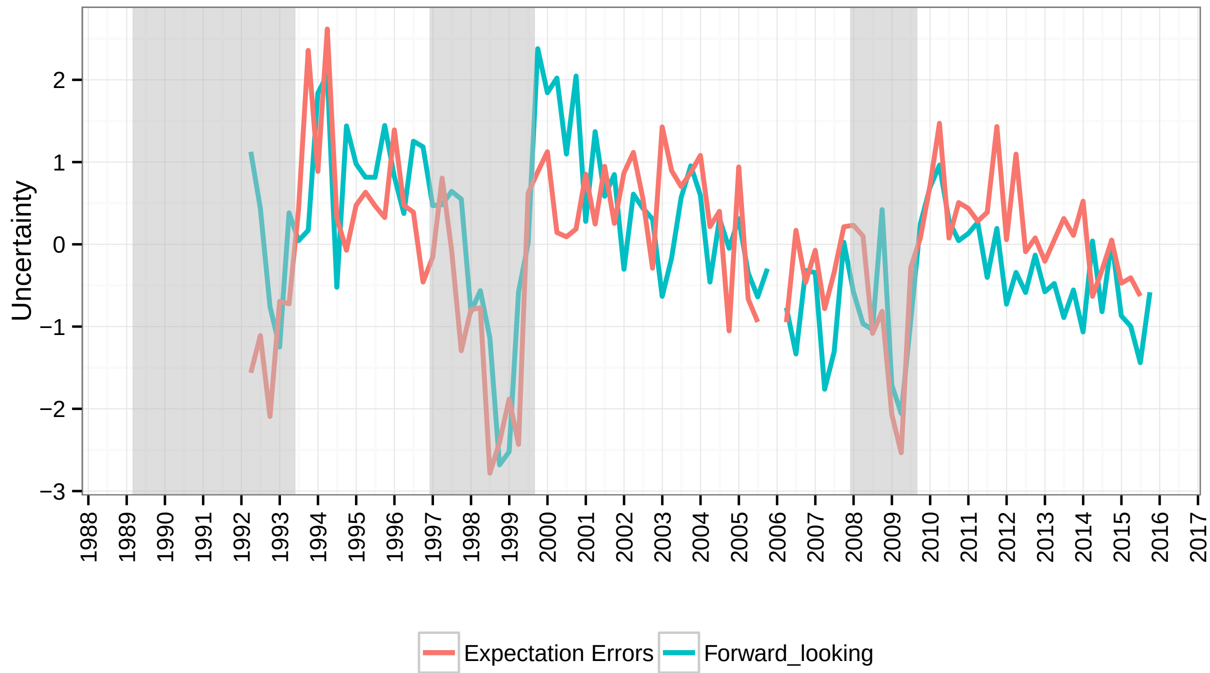

Figure 8: Unweighted Uncertainty Indicators

Given that the peaks and troughs in the uncertainty indicators coincide with potentially relevant political and economic events, the indicators seem plausible. They also broadly correspond to the significant events reflected in Redl (2015)'s uncertainty measure for South Africa based on forecaster disagreement, although their large movements seem to occur a few quarters later. In general the uncertainty indicators tend to decrease as the economy enters a recessionary period and then to increase towards the end of the recession and into the start of the recovery phase. This is probably because the majority of agents expect poorer general conditions with more certainty as the recession takes hold. Uncertainty about the future then increases around the trough, as expectations became more disperse and more uncertain.

7 Cyclical Analysis and Comovement

This section investigates the extent to which these confidence and uncertainty measures are associated with fluctuations in real activity.[27] Figure 9 illustrates the aggregate (unweighted) forward-looking confidence indicator, the uncertainty indicator based on expectations errors, and real GDP growth over the period. Real GDP growth is measures as annual quarter-on-quarter growth, i.e. 2015Q1

[27]George has also suggested looking at the non-response rate for a cyclical trend. Hart (2015) calculated the non-response rate by taking the number of firms which did not respond to a specific question as a fraction of the number of firms which returned the survey in each quarter. But I think George was perhaps referring the non-response rate in terms of questionnaires answered? In other words, the non-responses in terms of missing values or in terms of number of respondents out of total (1,500) mailed? We could investigate whether there a correlation between non-responses and uncertainty?

over 2014Q1, which corresponds to the reference period in the surveys. OECD sectoral production indices are also used as an alternative measure of real activity for the sectors.

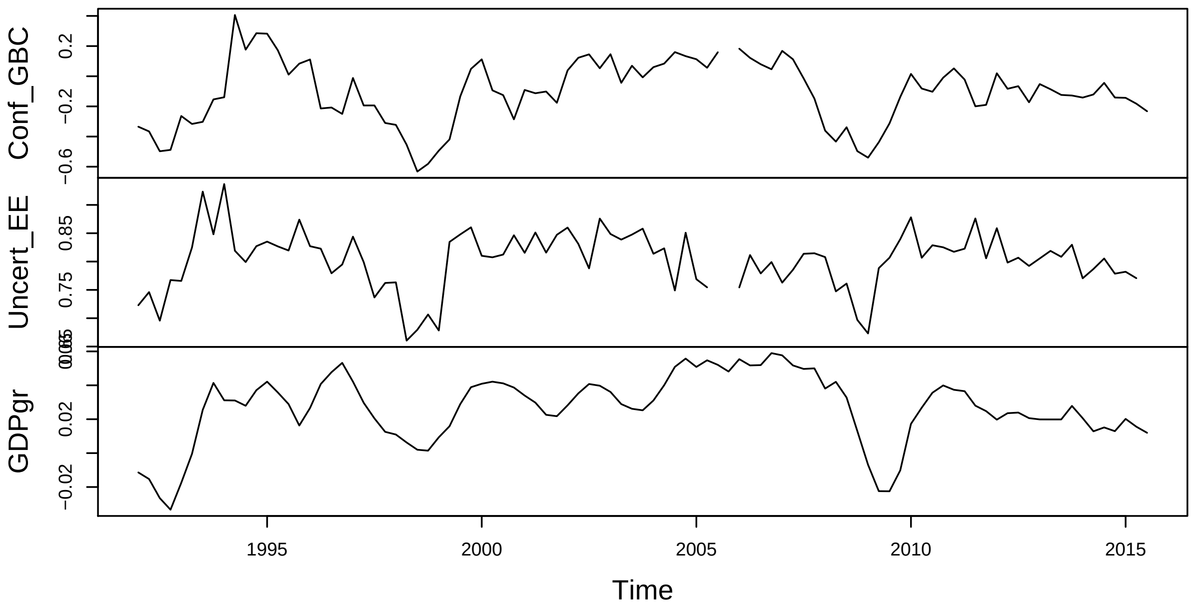

Figure 9: Confidence and uncertainty indicators and real GDP growth

These survey-based measures appear to plausibly capture confidence and uncertainty in South Africa. The confidence indicators appear to strongly pro-cyclical, and follow real GDP growth closely. The uncertainty indicators appear to fall sharply at the beginning of the recessionary period, and to rise sharply towards the end of the recession and into the recovery period. Surprisingly, these indicators of uncertainty do not appear to be contemporaneously counter-cyclical, as was the case for the majority of the uncertainty indicators in the international literature (e.g. Bloom, 2014). Indeed, they do not have a negative contemporaneous correlation with either real activity or confidence indicators as is the case in most of the literature.

Figure 10 illustrates the cross-correlograms for 4 of the (weighted) indicators and real GDFP growth. Confidence is significantly correlated with real GDP growth. The forward-looking measure seems to lead the activity measure and GDP growth. The highest correlation coefficient for the forward-looking measure occurs at 1 lag, whereas for the activity measure it occurs contemporaneously. As one would expect, the forward-looking confidence indicator seems to be a better candidate leading indicator.

The uncertainty indicators do not exhibit a negative contemporaneous correlation with real GDP growth. They are significantly negatively correlated with lagged real economic growth at 3-7 lags. This confirms the pattern exhibited above. Uncertainty seems to decrease significantly as the economy enters a recession, and spike towards the end of the recession or the beginning of the recovery period. The patterns are very similar for the unweighted versions of the indicators, although they often exhibit positive and mildly significant contemporaneous correlations. The patterns are also generally similar for the sectoral indicators and sectoral real GDP growth. In addition, the relationships between the sentiment indicators and both employment and investment exhibit very similar patterns.

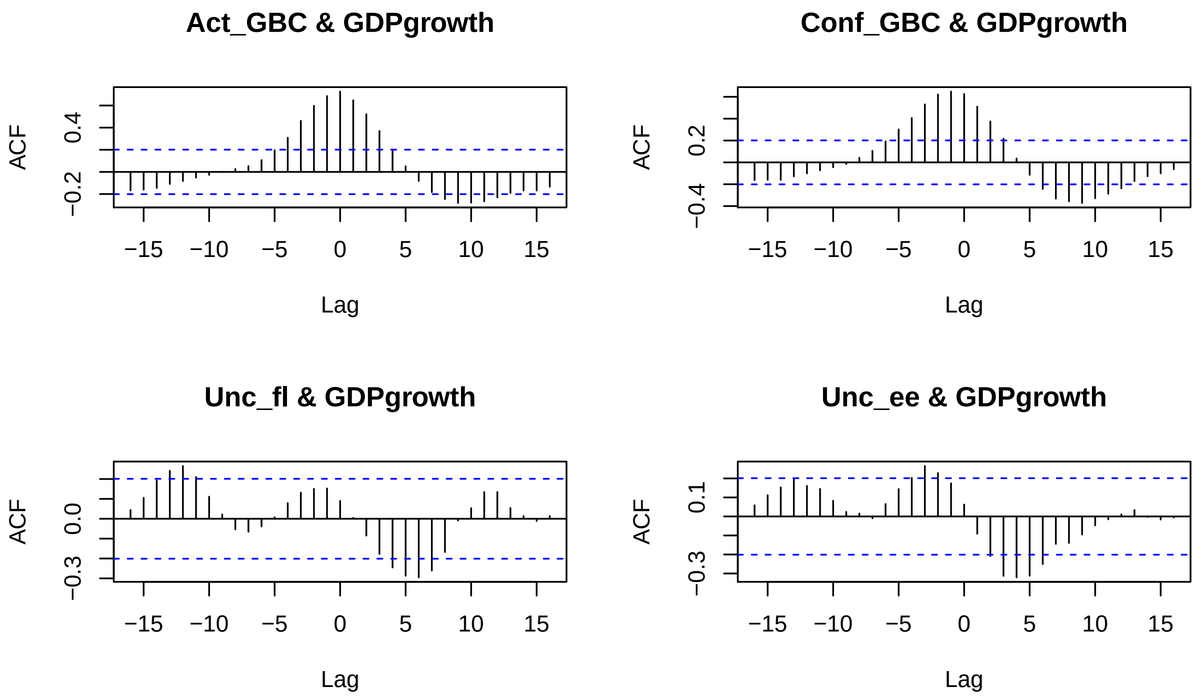

Figure 10: Cross-correlograms of confidence, uncertainty and real GDP growth

7.1 VAR Analysis

This section investigates the impact of shocks to confidence and uncertainty on real economic activity, using an agnostic vector autoregression (VAR) approach. Most macro variables move together over the business cycle, without any obvious causal direction. This makes it difficult to identify the direction of relationships. The literature has either assumed the direction of causation, or relied on timing for identification in estimators like VARs. This is problematic because of the contemporaneous movement of macro variables and the forward-looking nature of investment and hiring. It is not surprising that a wide range of results have been found using VAR regressions because of their sensitivity to subtle differences in assumptions (Baker and Bloom, 2013).

This section follows Bachmann, Elstner and Sims (2010) and Bachmann, Elstner and Sims (2013) in using standard recursive VARs to trace out the dynamic responses of economic activity to surprise increases in confidence and uncertainty. The aim is to investigate whether these measures have a significant dynamic relationship with real activity (i.e. output, employment and investment), and whether a shock to either of the measures generates responses which are in line with the theory.

The relationships are analysed for the aggregate variables, as well as for each sector separately. The advantage of also looking at specific sectors of the economy separately is that general equilibrium effects are likely to be mitigated. For instance, the “wait-and-see” effect is a partial equilibrium mechanism, which might be dampened by general equilibrium price adjustments (e.g. wages are likely to adjust in equilibrium so that at least some firms continue hiring). The focus on sector level data thus gives the wait-and-see mechanism a better chance of shining through (Bachmann, Elstner and Sims, 2010).

7.1.1 Methodology

The relationships are first investigated with bivariate recursive VARs featuring a measure of economic activity and an indicator of confidence or uncertainty respectively. A bivariate system is a parsimonious way to model the joint dynamics of sentiment and real economic activity (Bachmann, Elstner and Sims, 2013). A range of VARs are estimated on the quarterly data running from 1992Q1 to 2015Q3. The confidence and uncertainty indicators enter in levels, while the activity variables enter as annual quarter-on-quarter growth rates, which corresponds to the survey reference period.[28] Unit root test indicate that virtually all of the series are stationary, assuming of a drift parameter.

The specification aims at providing preliminary evidence on the dynamic effects of confidence and uncertainty shocks on real activity. In the bivariate case, both variables are treated as endogenous:

$$y_t = \beta_{10} - \beta_{12} z_t + \gamma_{11} y_{t-1} + \gamma_{12} z_{t-1} + \epsilon_{yt}$$

$$z_t = \beta_{20} - \beta_{21} y_t + \gamma_{21} y_{t-1} + \gamma_{22} z_{t-1} + \epsilon_{zt}$$

where y is activity (output, employment or investment), z is sentiment (confidence or uncertainty), and ϵ is the residual of each equation.

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 (i.e. no serial correlation, homoscedasticity and normality) are satisfied. In the majority of cases the information criteria point to 2 lags. The model fit is best when a constant term is included. At present, simple linear interpolation is used for the missing values.

The sentiment indicators are ordered second in a recursive identification strategy, with the Cholesky decomposition used to identify structural shocks. With this ordering, shocks to the sentiment indicator are allowed to have a contemporaneous impact on activity, but shocks to activity have no contemporaneous impact on sentiment ($\beta_{21} = 0$). In other words, innovations to the sentiment indicators influence economic activity on impact, but not vice versa.

This allows for the generation of impulse response functions (IRFs), which show the dynamic impact of a shock to either confidence or uncertainty on the system. The shock itself is an innovation to the residual in the equation of the variable of interest. The importance of innovations can also be examined with variance decompositions. While the IRFs describe the reaction of a variable of interest to some exogenous shock, the decomposition of the forecast error variance of a given variable determines how much of the error can be explained by exogenous shocks to the other variables in the system (Girardi and Ruiter, 2015).

[28] In contrast, Bachmann et al (2013), Jurado et al (2015) and Girardi et al (2015) use the real activity variables in (log) levels, while Bloom (2009) uses a HP filter to de-trend the variables. I think we should probably have versions in (log) levels, in order to compare IRFs more closely and to uncover potential longer term relationships? I assume this would involve some cointegration work, but the papers mentioned above are not very clear on the specifics of their estimations.

7.1.2 Granger causality tests

Granger causality tests are often performed when investigating the comovement among variables. This test determines 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. A time series Z is said to Granger-cause Y if it can be shown that the Z values provide statistically significant information about future values of Y.

Pellissier (2002) used Granger causality tests to investigate the relationship between the RMB/BER business confidence index and the coincident business cycle indicator. The results suggested a coincident relationship between the two series, rather than a leading relationship. However, Pellissier (2002) argued that business confidence as measured by RMB/BER business confidence index did exhibit leading indicator attributes in terms of its timely availability and the finality of its data.

Table 3 reports the results for Granger causality tests for the sentiment indicators and real GDP growth. The results suggest that lagged confidence significantly predicts real GDP growth, and vice versa. Hence, there seems to be a high level of feedback between all three measures of confidence and real GDP growth. The forward-looking confidence indicator has the highest test statistic, suggesting that it is the best candidate for a leading indicator of the business cycle.[29] This is also the case for the confidence indicators at sector level.

The results indicate that the weighted uncertainty indicators do not Granger-cause real GDP growth, although there is mild evidence that the unweighted indicator significantly predicts real GDP growth. In contrast, there is some evidence that lagged real GDP growth Granger-causes the uncertainty indicators based on expectations error. The findings for the sectoral indices are similar. These preliminary results imply that there is no "causal" relationship between these measures of uncertainty and real GDP growth. If anything, movements in uncertainty seem to follow movements in real activity growth.

Table 3: Granger causality tests

Granger causality H0:	statistic	p-value
Conf_CC do not Granger-cause RGDPGrowth	3.939**	0.02
RGDPGrowth do not Granger-cause Conf_CC	3.563**	0.03
Act_GBC do not Granger-cause RGDPGrowth	2.351*	0.10
RGDPGrowth do not Granger-cause Act_GBC	2.95*	0.06
Conf_GBC do not Granger-cause RGDPGrowth	4.316**	0.01
RGDPGrowth do not Granger-cause Conf_GBC	2.645*	0.07
Uncert_fl do not Granger-cause RGDPGrowth	0.605	0.55
RGDPGrowth do not Granger-cause Uncert_fl	1.375	0.26
Uncert_ee do not Granger-cause RGDPGrowth	0.552	0.58
RGDPGrowth do not Granger-cause Uncert_ee	2.908*	0.06
unw.Uncert_ee do not Granger-cause RGDPGrowth	3.004*	0.05
RGDPGrowth do not Granger-cause unw.Uncert_ee	3.341**	0.04

7.1.3 Results: Confidence

Figure 11 illustrates the IRFs of a bivariate VAR with the forward-looking confidence measure and real GDP growth. The left panel plots the responses of real GDP growth to an orthogonal

[29] We could investigate this further, as I discuss below.

shock in the confidence measure, with 95% bootstrap confidence intervals. Following an increase in confidence, real GDP growth increases by almost 0.2% on impact, with a peak at 1 year. The effect on the growth rate is transitory, dying out after approximately 7 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)).[30] The right panel plots the responses of confidence to an orthogonal shock in real GDP growth. Following an increase in real GDP growth, there is a significant increase in confidence of around 2% in the following quarter. The results are similar for alternative orderings (as the correlations in errors are only around 0.3).

The IRFs for the other two confidence indicators based on current conditions (not illustrated here) are almost identical. The impact is also positive and significant for all of the sectoral measures on real output growth, based on sectoral GDP and production indices. The IRFs when using growth in employment and investment as the measures of real activity are also qualitatively similar.

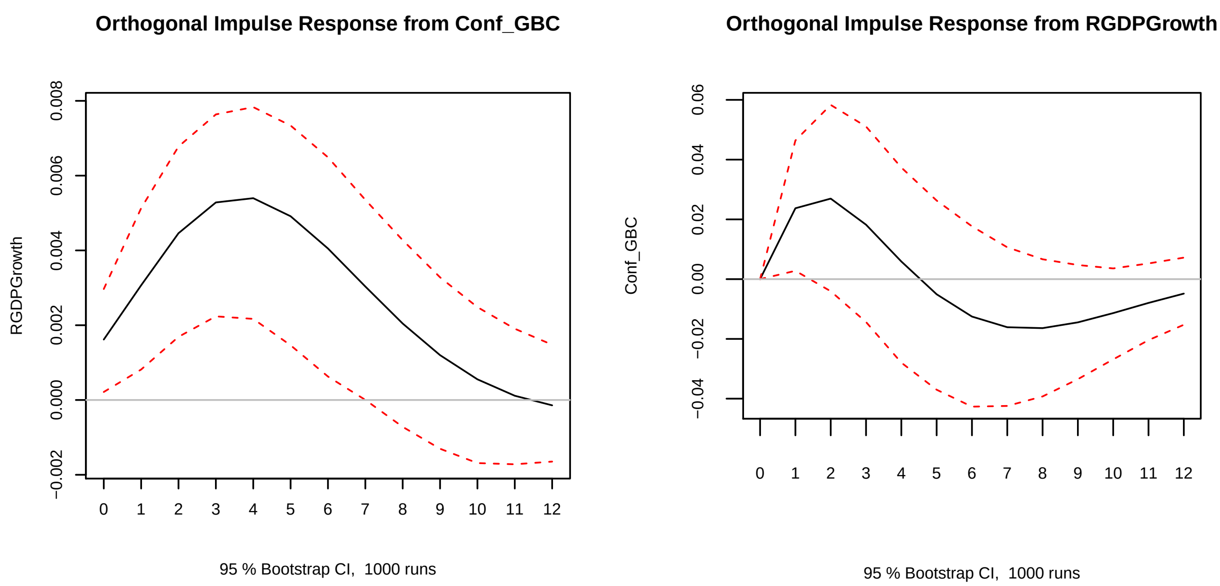

Figure 11: IRFs of confidence (forward-looking) and real GDP growth

The forecast error variance decomposition (FEVD) tells us the proportion of the movements in a sequence due to its “own” shocks versus shocks to the other variable. The FEVDs show that up to around a third (37%) of the movements in real GDP growth are explained by the various confidence indicators over the longer term, while real GDP explains up to 7.5% of the variance in confidence.[31]

The results show that there is a strong relationship between the confidence indicators and real activity, measured as real GDP growth, as well as real growth in employment and investment. This is the case for the aggregate indicators as well as the sectoral indicators. This implies that the confidence indicators contain useful information about current and future economic developments. As a results, these confidence indicators are potentially useful for monitoring economic developments

[30] As I discuss below, the next step would probably be to include confidence in a larger VAR system that controls for a number of economic fundamentals, to see if it still has a significant impact.

[31] We could illustrate the FEVDs here?

in a timely manner and for forecasting future economic activity.[32]

7.1.3.1 *Potential Further Analyses*

The analysis above could be expanded by analysing the leading and coincident indicator properties of the confidence indicators. In particular, this section could try to establish whether the forward-looking confidence indicator is more suitable leading indicator than the published RMB/BER business confidence index, as well as other measures like the SACOB index. This is important given that the RMB/BER business confidence index is currently used by the SARB as a component series in the official leading indicator.

One possibility to investigate the leading and coincident indicator properties of the series is to follow Boshoff (2005). He described the cyclical properties of financial variables in terms of duration, amplitude and steepness, and then analysed the co-movement between cycles in these variables and the business cycle using the concordance index. 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. The mean-corrected concordance statistic was used to investigate co-movement of both classical and growth rate cycles. The consistency of lead time intervals between turning points could then be analysed and compared to alternative indicators.

Another option is to follow Taylor and McNabb (2007), who used the methodology developed by Haan (2000) to analyse comovement between confidence indicators and the business cycle. This method provides an alternative framework for examining correlations between series based on correlations from VAR forecast errors at different horizons. This approach can accommodate both stationary and integrated variables and does not require pre-filtering. Furthermore, the method does not require the identification restrictions needed for VAR decompositions. Bivariate VARs are estimated in levels with output and confidence (with and without time trend). The h-step ahead forecasts are estimated and used to calculate the h-step ahead forecast errors, for both output and confidence. The correlation between these two forecast errors is the primary statistic of interest. Taylor and McNabb (2007) found that across countries the correlation between output and confidence was significant and the correlation was predominantly positive for a forecast horizon of 8 quarters ahead, implying that confidence indicators are pro-cyclical leading indicators.

A related avenue for investigation would be to assess the usefulness of the indicators in terms of forecasting and predictive power. Specifically, this section could analyse whether the indicators are useful in predicting recessions, whether they improve forecasts even after controlling for fundamentals, and whether they are useful for now-casting, given that they are available around two months before many official series.

Taylor and McNabb (2007) tested the predictive power of confidence indicators. First, they investigated the power of confidence indicators in predicting the likelihood of an economic downturn as a discrete event. Second, they used a VAR analysis to assess out-of-sample quantitative point forecasts of GDP growth, to test whether forecasting errors were significantly reduced by the inclusion of the confidence indicators. The results showed that there was a significant role for confidence indicators in predicting below-average growth. The confidence indicators therefore had predictive power and added forecasting ability over and above other leading indicators in the UK and the Netherlands. This test could be implemented here to gauge the usefulness of the confidence indicators derived from the BER surveys.

[32] We could investigate this further, as I discuss below.

An extension would be to test whether the relationship is non-linear and asymmetric, depending on the size or duration of the change in confidence. The forecasting ability of confidence indicators might be completely offset by other indicators during ordinary times, while increasing notably in the presence of unusual events. Moreover, the relation during a recovery (and potentially late stages of a recession) may be different from the relation during the rest of an expansion.

7.1.4 Results: Uncertainty

Figure 12 illustrates the IRFs of a bivariate VAR with the uncertainty indicator based on expectations errors and real GDP growth. The left panel plots the responses of real GDP growth to an orthogonal shock in the uncertainty measure, with 95% bootstrap confidence intervals. A shock to uncertainty is followed by a positive but insignificant increase in real GDP growth. This is contrary to most of the literature (e.g. Bachmann, Elstner and Sims (2013) and Redl (2015)), which finds that in bivariate VARs, innovations to uncertainty have protracted negative effects on economic activity.

The right panel plots the responses of uncertainty to an orthogonal shock in real GDP growth. Following a shock to real GDP growth, there is a significant negative response in uncertainty, but only between 4 and 8 quarters later. This confirms more formally the graphical results above, as well as the findings for the correlation analysis and the Granger causality tests. When real GDP growth decreases, as in a recession, uncertainty increases after around 4 quarters, with the impact dying out at around 8 quarters. The results are similar for alternative orderings (as the correlations in errors are only around 0.1).

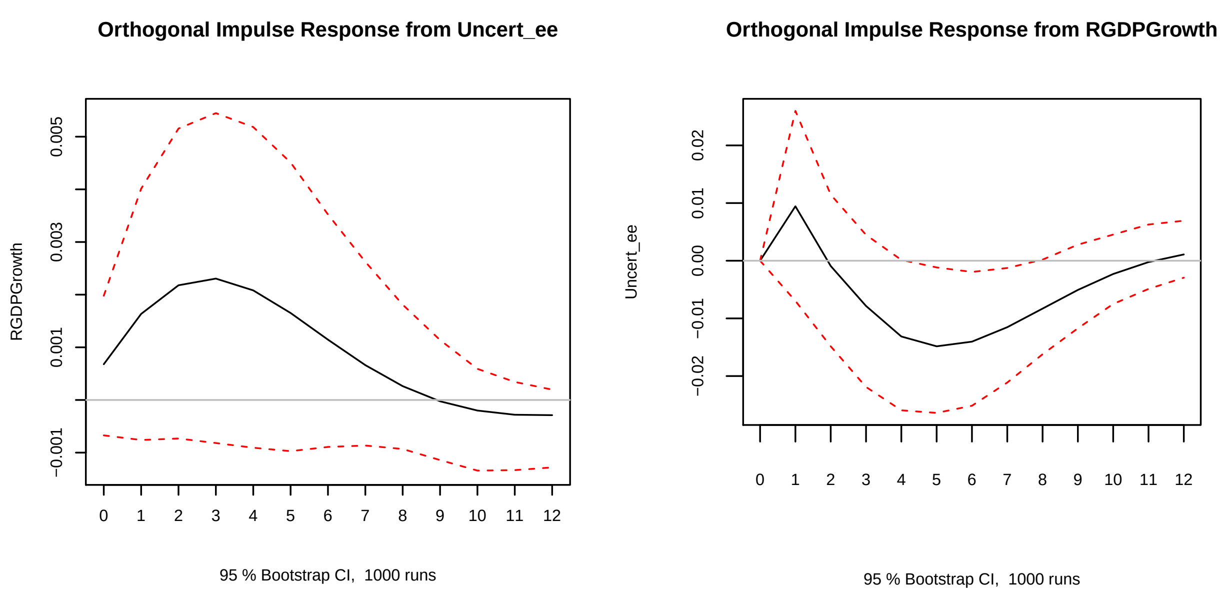

Figure 12: IRFs of weighted uncertainty (expectations errors) and real GDP growth

The IRFs for the forward-looking uncertainty indicators look almost identical, as do the IRFs when using growth in employment and investment as measures of economic activity. The IRFs for the sectoral uncertainty indicators are usually insignificant. The FEVDs show that the contributions of the different uncertainty series to the variance decomposition of real GDP growth are relatively small, at around 10% over longer forecast horizons, and vice versa.

These uncertainty indicators do not exhibit the typical timing of the relationship with real economic activity found elsewhere. Indeed, the results are even more contrary when the unweighted uncertainty indicators are used. Figure 13 illustrates the IRFs of a bivariate VAR with the unweighted uncertainty indicator based on expectations errors and real GDP growth. The response of uncertainty to an orthogonal shock in real GDP growth (right pane) is very similar. However, the response of real GDP growth to an orthogonal shock in the uncertainty measure is now even more positive and significant at 2-3 lags. The timing of the relationship does not provide any evidence for a causal impact from uncertainty to real GDP growth and are not consistent with the wait-and-see mechanism. If anything, the results imply that GDP growth negatively affects uncertainty with a lag.

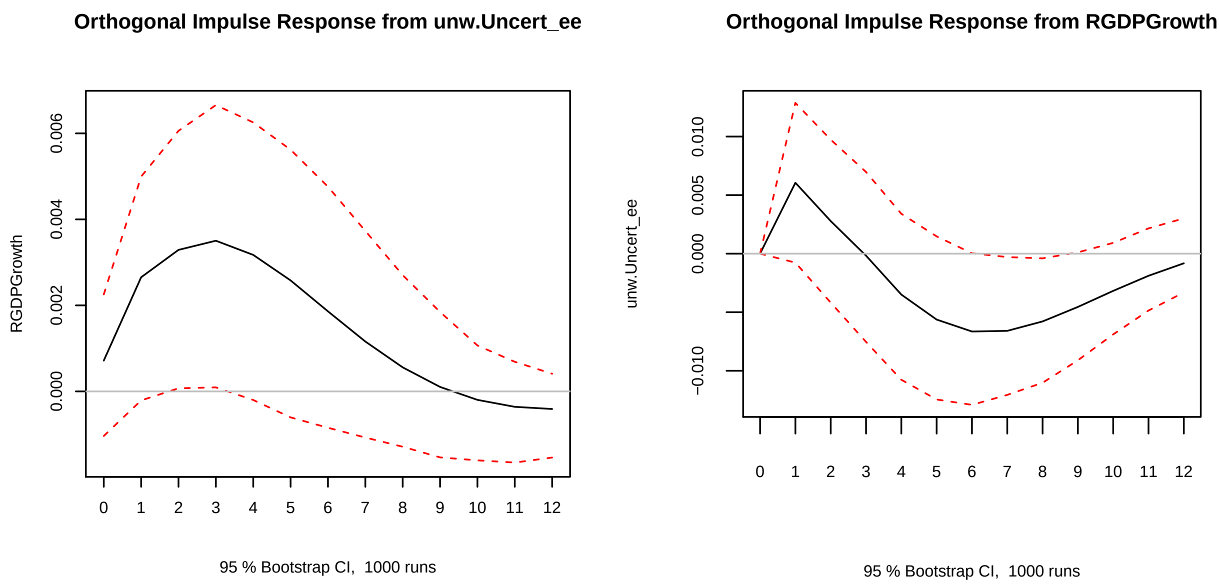

Figure 13: IRFs of unweighted uncertainty (expectations errors) and real GDP growth

It is somewhat of a puzzle why these uncertainty indicators derived from the BER business tendency surveys do not exhibit the typical timing of the relationship with real economic activity found elsewhere. However, there are a number of potential further avenues to investigate.

7.1.4.1 *Potential Further Analyses*

One reason for the puzzle could be that the bivariate VARs, though instructive, are misspecified (Girardi and Ruiter, 2015). In order to test this, one could extend the baseline setup by including a number of additional series in the models. A number of authors have investigated the impact of uncertainty in larger VAR systems (see e.g. Bloom, 2009, Bachmann, Elstner and Sims (2013), Redl (2015)). The additional variables typically include the stock market index, the money market rate, credit spreads, the CPI, earnings, employment, production and investment. The ordering is based on the assumption that shocks instantaneously influence the stock market, then prices (interest rates, inflation and wages), and finally quantities (employment, investment and output). The VARs are then typically estimated in (log) levels, as opposed to the growth rates used above, which may allow longer term relationships to emerge. The larger models would also include more lags, which might allow some more feedbacks to emerge. For instance, a recession might trigger an increase in uncertainty, which might in turn hamper the recovery.

An extension would then be to follow Bachmann, Elstner and Sims (2010), by restricting the long run impact of uncertainty to zero, in the spirit of Blanchard and Quah (1989). The idea is the wait-and-see effect would not influence economic activity in the long run. The hope is that the short run impact of uncertainty will shine through when the long run impact is "switched off". A related hypothesis to be tested is whether there is asymmetry in the frequency horizon of shock effects. Deeper or systemic shocks may be associated with medium-term, rather than high-frequency fluctuations in output and the absence of 'wait-and-see' effects in recent models may be due to their particular treatment of 'short run' and 'long run'. In order to test these hypotheses, one would probably have to estimate the VAR systems in (log) levels.

Some authors have added measures of confidence to estimate three-variable VARs. Girardi and Ruiter (2015) argued that uncertainty (or "second moment") shocks may coincide with confidence (or "first moment") shocks. To address whether uncertainty simply picked up the effect of changes in confidence, they included a measure of confidence in a three-variable VAR system, with confidence ordered first under a recursive identification scheme. Bachmann, Elstner and Sims (2010) argued that confidence is informative about economic activity in the long-run. Making uncertainty orthogonal with respect to confidence could control for the long-run predictive component of uncertainty, thereby making it more likely to reflect the high-frequency impact of uncertainty.

Figure 14 and Figure 15 illustrate preliminary results from three-variable VARs including (forward-looking) confidence, (expectation error) uncertainty and real GDP growth. The results are very similar to the IRFs for the bivariate VARs reported earlier. A shock to confidence is followed by a significant positive increase in real GDP growth, whereas a shock to uncertainty is not followed by lower output growth. In contrast, a shock to real GDP growth is not followed by a significant increase in confidence, but is followed by a decrease in uncertainty around 4 quarters later. In other words, recessions are followed by an increase in uncertainty with a lag. According to Bachmann, Elstner and Sims (2010), recessions are times of severed relationships and failing business models. Bad economic outcomes breed uncertainty, as these relationships have to be re-established and business practices have to be re-arranged. Thus, uncertainty could be interpreted as an epiphenomenon that accompanies poor economic outcomes.

Although these larger VAR systems should be investigated, it is not clear that these larger systems will change the fundamental timing of the relationship between the survey-based uncertainty indicators and real activity. Changes in the uncertainty indicators will most likely still not lead changes in growth, as they do in other countries, which means that they cannot have a (Granger) causal impact (in terms of timing).

Another reason for the apparent puzzle could be that the survey-based uncertainty indicators are very noisy and do not reflect the most important episodes of uncertainty well. In attempt to deal with such noisy data, one could smooth the indicators, or follow Bloom (2009) in creating dummy variables for periods of abnormally high uncertainty, defined as spikes in uncertainty which are more than one standard deviation above the mean. The idea is to ensure that identification comes only from these large and arguably exogenous uncertainty shocks, rather than from the smaller ongoing fluctuations.

An extension would be to test whether the relationship is non-linear and asymmetric, depending on

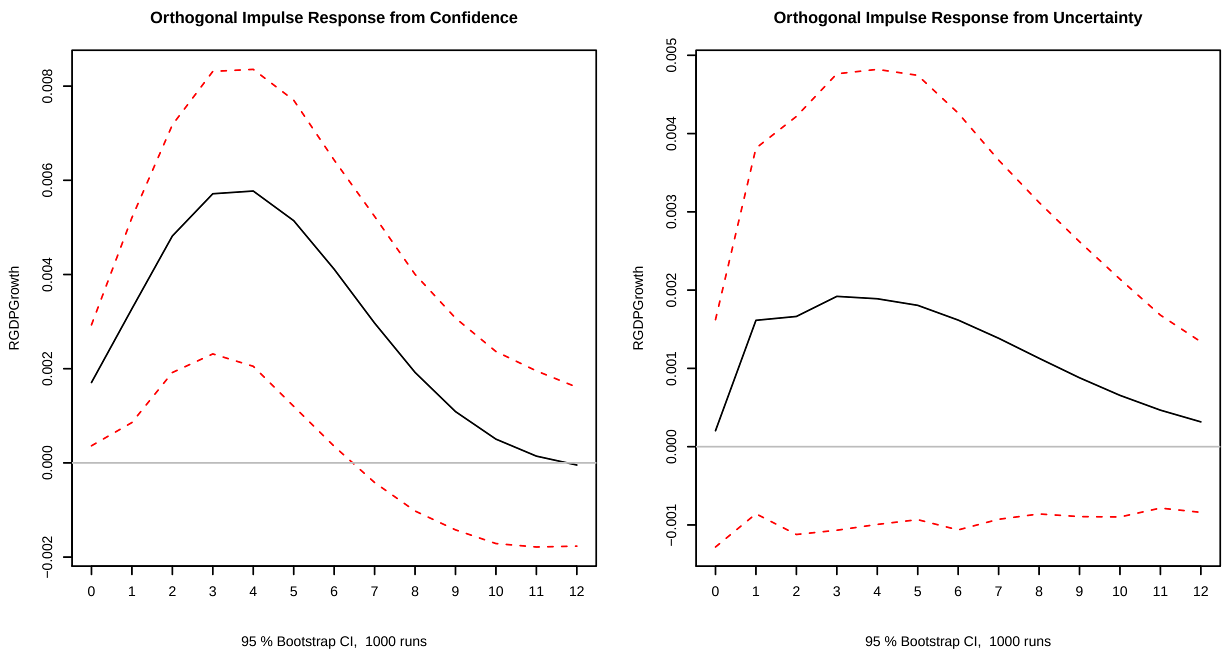

Figure 14: IRFs of real GDP growth to confidence and uncertainty

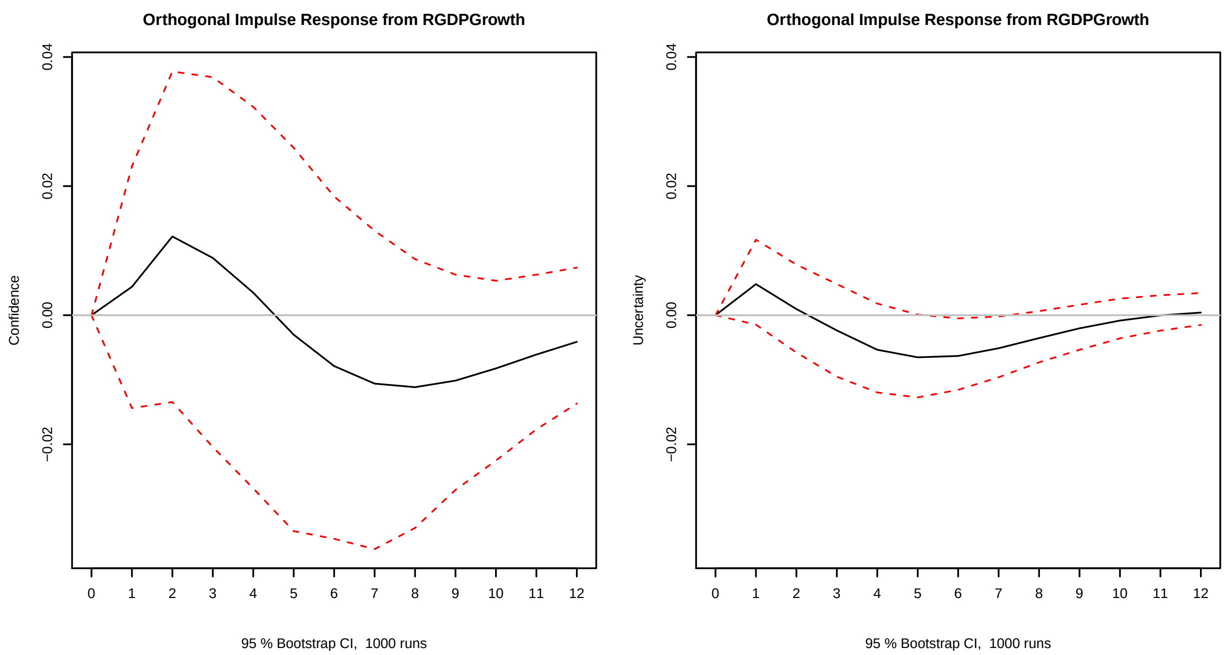

Figure 15: IRFs of confidence and uncertainty to real GDP growth

the size or duration of the change in uncertainty. For instance, shocks to uncertainty might only play an important role during episodes of economic tensions. Large increases in uncertainty may be more important in predicting future changes in activity than large decreases. One could also test whether the relationship is asymmetric over the different phases of the business cycle. The relation during a recovery may be different from the relation during the rest of an expansion.

Another possibility is to aggregate the survey results differently. For instance, Jurado, Ludvigson and Ng (2015) recommends that indicators of uncertainty should reflect the common variation across many series. One could therefore combine the responses to various forward-looking questions to form a composite series. Alternatively, one could follow Jurado, Ludvigson and Ng (2015) in removing the forecastable component of each series and using the volatility of forecast errors as the indicators.

These are certainly potential avenues for investigation. However, it is not clear that these alternative versions of the uncertainty indicators (e.g. dummies or composite series) will change the fundamental timing of the relationship between the uncertainty indicators and real activity. The uncertainty indicators will most likely still not lead changes in growth, as they do in other countries.

It may be that the frequency of the data is too low to reflect higher frequency movements in uncertainty. For instance, uncertainty may spike in the first month of a quarter (e.g. January), at the same time as a fall in GDP growth. Yet when the quarterly survey results are collected in the last month of the quarter (e.g. March), the uncertainty indicator may have already rebounded or decreased relative to the previous quarter. However, this would not concur with the protracted negative effects usually found in the literature.

It is possible that there is a structural explanation for this peculiar relationship in South Africa. It might be that South African firms are different from international firms. They may react to events like recessions later than US firms for instance (i.e. they may be less forward-looking). Alternatively, it could be that something like the growth effect or the Oi-Hartman-Abel effect is in operation in South Africa. But such an explanation would contradict the findings in Redl (2015) for uncertainty in South Africa.

There may be problems with the survey data. It could be that there are too many errors in the data or that the respondents are not representative of the economy. However, the confidence indicators seem to reflect real activity well, implying that the surveys are capturing one form of sentiment accurately. It is possible that respondents use an incorrect reference period when answering the survey questions, potentially leading to a mismatch in reference periods. This would be more likely to affect the expectations error uncertainty indicators. However, the indicators based on cross-sectional dispersion of forward-looking responses also exhibit the puzzling timing in their relationship with activity growth. Moreover, the results do not seem more plausible when using real activity measures with different reference periods, such as quarter-on-quarter growth rates.

Another avenue of investigation is to compare the survey-based uncertainty indicators to other measures of uncertainty, such as stock market volatility, the corporate bond spread, and potentially the two uncertainty indices derived for South Africa by Redl (2015) and McClean (2015). These alternative measures of uncertainty can then be related to measures of real economic activity, in order to examine whether the findings are more consistent with the literature.

8 Conclusion

The paper contributes to the literature by calculating indicators of business sentiment for South Africa from the BER business tendency surveys. The aim is to investigate whether it is possible to derive plausible indicators for confidence and uncertainty from the microdata. The confidence indicators seem plausible and have a significant relationship with real activity growth. Further analysis could investigate whether these indicators are useful as leading indicators, and for forecasting and prediction. The uncertainty indicators seem plausible at face value. However, they do not exhibit a relationship with real activity growth that is consistent with the literature. Further analysis could investigate this relationship further with alternative proxies and larger VAR systems.

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