Business Sentiment and the Business Cycle in South Africa

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The global financial crisis and subsequent Great Recession were associated with low levels of confidence and heightened uncertainty. This has motivated a large body of international literature investigating the impact of changes in business sentiment, and especially uncertainty, on real economic activity. Yet to date there has been little research on business sentiment in South Africa. This paper attempts to make two contributions to the literature. The first is to construct new composite indicators of confidence and uncertainty for South Africa, based on the microdata from the BER's business tendency surveys. The second is to examine the comovement between the sentiment indicators and economic activity. The aim is to examine whether these survey-based indicators have plausible and significant relationships with real economic output. The composite sentiment indicators seem plausible and the results confirm the findings in the literature. The composite confidence indicators exhibit a significant positive correlation with real GDP growth and seem to contain relevant information for predicting output growth. The composite uncertainty indicators exhibit a significant negative correlation with real GDP growth and a shock to uncertainty is generally followed by a decrease in real GDP growth.

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1 Introduction

The global financial crisis and subsequent Great Recession were associated with exceptionally low levels of confidence and heightened uncertainty. According to the ECB (2013), this weak business sentiment contributed to a large extent to the Great Recession and the subsequent recovery was characterised by only modest improvements in business sentiment. More recently, uncertainty has increased sharply in the wake of Britain's EU referendum (Stewart, De and Cole, 2016) and the US presidential election (Rampell, 2017). This has motivated a large body of literature investigating the impact of changes in business sentiment, and especially uncertainty, on real economic activity.

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.

Empirical work on business sentiment faces two main challenges. The first is that sentiment is an elusive concept that is difficult to define precisely or measure directly, which makes it difficult to construct proxies for confidence and uncertainty. The second is that it is challenging to identify the impact of measures of confidence and uncertainty on real economic activity.

Macroeconomic theory postulates a potential causal link between confidence and economic activity,

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based on multiple equilibria in which self-fulfilling expectations of subjective agents generate changes in real activity. Yet even if confidence indicators do not provide causal information on the business cycle, their leading indicator 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. 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. 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. This may be due in part to the difficulties surrounding the measurement of uncertainty.

To date there has been little research on business sentiment in South Africa. It is important to confirm the existence and nature of the relationship between sentiment and economic activity in developing countries, which are often characterised by higher business uncertainty than developed countries (Bloom, 2014). Not only is South Africa an emerging market, but its tumultuous political history and the legacy of Apartheid has contributed significantly to business uncertainty.

This paper attempts to make two contributions to the literature. The first is to construct new composite indicators of confidence and uncertainty for South Africa, based on the microdata from the BER's business tendency surveys. Although measuring economic sentiment is not straightforward, 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. Moreover, these indicators are often available earlier (with a shorter lag) than official statistics and are usually not subject to revisions (ECB, 2013).

The second contribution is to examine the comovement between the sentiment indicators and economic activity, using the standard agnostic econometric methods (VARs) employed elsewhere. The aim is to examine whether these survey-based indicators have plausible and significant relationships with real economic activity. As the indicators are calculated at sectoral level as well, 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).

The composite confidence indicators exhibit a significant positive correlation with real GDP growth and seem to contain relevant information for predicting output growth. Shocks to the confidence indicators are followed by a significant increase in real GDP growth. The new confidence indicators also seem to outperform the existing confidence measures for South Afrca. The composite uncertainty indicators exhibit a significant negative correlation with real GDP growth. Shocks to uncertainty are followed by a decrease in real GDP growth. The composite sentiment indicators therefore seem plausible and will hopefully prove useful for a range of future applications.

2 Confidence

This section provides a brief review of the literature on business confidence. Pellissier (2002) described business confidence as the *"degree of sentiment towards risk taking by business for whatever reason."* Business confidence involves agents' perceptions of the current and expected future business climate. It can be interpreted as the relative optimism or pessimism among firms regarding *current conditions* and expected *future developments*, with the former probably influencing the latter. Changes in perceptions of economic developments could reflect psychological factors, or be related to the release of information (news) regarding future development not yet captured by economic fundamentals, and not summarised by contemporaneous macroeconomic variables. Changes in confidence may become a source of economic fluctuations through its impact on consumption and investment decisions (Mendicino and Punzi, 2013).

2.1 Theoretical Links

The idea that aggregate economic activity might be driven in part by psychological factors, such as confidence and changes in expectations, played an important role in early business cycle theories. Beveridge (1909) was among the first to stress expectations as an underlying factor in business cycles. Any change in expectations about demand and profits might lead firms to increase their production, resulting in a phase of overproduction. Excess optimism about future demand leads to a wave of pessimism, generating cyclical fluctuations (ECB, 2013).

According to Pigou (1927), "*varying expectations of business men.constitute the immediate cause and direct causes or antecedents of industrial fluctuations.*" Psychological factors, such as waves of optimism and pessimism, lead entrepreneurs to make errors when forming their expectations about future profits. These errors generate cycles through rises and falls in investment (Leduc, 2010). Keynes (1936) also argued that sentiment plays a large role in driving economic activity: "*Our decisions to do something positive, the full consequence of which will be drawn out over many days to come, can only be taken as a result of animal spirits - of a spontaneous urge to action rather than inaction, and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities.*" According to this theory, sentiment plays a key role in explaining economic fluctuations (Mendicino and Punzi, 2013).

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 supposes that a 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 contemporaneous macroeconomic variables. 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 matter (Taylor and McNabb, 2007).

2.2 Empirical Findings

Notwithstanding the popularity of confidence indicators with analysts, the stance of the empirical literature is more ambiguous. The findings 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). There are two main challenges when it comes to empirical work on business confidence: to construct proxies for confidence and to measure the impact of confidence on real economic activity.

2.2.1 Measuring Confidence

Confidence is an elusive concept, which is cannot be observed or measured 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 future developments. The assumption is that before a specific business activity is implemented (e.g. new production plans, employment, or purchases), some 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 statistics become available. Moreover, they are not subject to revisions and are useful in avoiding trend and seasonality problems.

The most common and widely used method to summarise or aggregate survey responses 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

[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).

approach (Nardo, 2003).[4] However, these approaches usually require actual quantitative reference series for the relevant variables, which is very restrictive in the case of business confidence, where quantitative reference series are not available. Moreover, the fact that they are linked to a reference series, 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. They found that the balance statistic was a satisfactory method of transforming the survey responses on output, investment, and exports.

Composite confidence indicators are typically derived from multiple questions in sector-specific surveys. The sector indicators are then aggregated to form aggregate composite indicators. As no single cause explains all cyclical fluctuations over the long term, it necessary to have signals for many possible causes of cyclical change, i.e. to use all potentially important information (Aarle and Kappler, 2012). Composite indicators, as opposed to answers from a single question, may have fewer false alarms and fewer missed turning points than individual components and tend to have more stable lead-times. They have the capacity to react to various sources of economic fluctuations, while being resilient to fluctuations affecting single components (ECB, 2013). Composite indicators typically include questions on prevailing conditions as well as expectations, although the recent literature suggests a distinction between indicators of current activity and forward-looking indicators (Bachmann, Elstner and Sims, 2010).

The European Commission builds composite indicators by aggregating the survey responses from 5 sectors, using multiple questions on current conditions and expectations. 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 to questions relating to the present and future business situation and stocks (with an inverted sign) (OECD, 2003). The aggregate 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).

Composite confidence indicators are now calculated by most countries. A prominent example is the Ifo Business Climate Indicator, which is a leading indicator in Germany. 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. The results for the manufacturing, construction, wholesaling and retailing sectors are weighted according to the importance of the industry. Another example is the Italian Economic Sentiment Indicator. It is based on the set of balances from surveys of industry,

[4] The probabilistic 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.

construction, services and retail trade, which are normalised and weighted with value added shares. Other composite confidence indicators include those published by the University of Michigan for the US, and the general climate indicator for the Japanese productive sector constructed by the Bank of Japan based on the Tankan Survey (INIS, 2014).

Various confidence indices have been used in the literature. Taylor and McNabb (2007) and Mendicino and Punzi (2013), for instance, used the composite confidence indicators based on the European Commission surveys for a number of European countries. Bachmann, Elstner and Sims (2010) and Bachmann, Elstner and Sims (2013) used the Philadelphia Fed's Business Outlook Survey and the German Ifo Business Climate Survey to calculate indices of current activity, as well as forward-looking indices. Barsky and Sims (2012) used the Michigan Survey of Consumers to construct a forward-looking measure of confidence. Kabundi (2004) used a dynamic factor model to extract the common components from the French Statistics Institute's business survey data.

Two indicators of confidence are published in South Africa: the RMB/BER Business Confidence Index (BER BCI) and the South African Chamber of Commerce and Industry Business Confidence Index (SACCI BCI). The BER BCI, discussed in more detail below, is constructed from the BER's quarterly business tendency surveys, which are similar to the business tendency surveys conducted all over the world. The BER BCI is constructed from a specific question that appears in all of the surveys (Q1): *"Are prevailing business conditions: Satisfactory, Unsatisfactory?"* The BCI is the weighted percentage of respondents that rated prevailing business conditions as *"Satisfactory"* and is therefore based on the perceptions of business people. All the survey responses are weighted (except the building survey), and the BER BCI is calculated as the unweighted mean of five sectoral indices. The BER BCI is an index of current economic activity, as opposed to forward-looking expectations, which is independent of external macroeconomic variables (Pellissier, 2002).

The SACCI BCI, formerly known as the SACOB BCI, is a composite index of 13 quantitative sub-indices that have been judged to have the greatest bearing on the business mood. These include the exchange rate, inflation, the prime rate, retail sales volumes, credit extension, commodity prices, import and export volumes, new vehicle sales, utility services, manufacturing production, building plans passed, and the stock market index. The SACCI BCI is an *ex post* measure of actual activity, which is dependent on external macroeconomic variables. The rationale is that recent business activity is indicative of the degree of business confidence (SACCI, 2011). In this sense the SACCI BCI is a composite measure of economic activity, rather than a confidence indicator in the way it is defined in the literature.

2.2.2 The Impact of Confidence

The majority of studies seem to find a significant positive relationship between confidence indicators and economic activity, although this does not necessarily imply a causal relationship. In general, the survey-based confidence indicators appear to be valuable leading indicators of the business cycle. Particularly when they are based on forward-looking questions, these indicators may include some information that is not available in other economic variables (ECB, 2013).

Confidence indicators also seem to provide valuable information for forecasting economic activity and they are widely used as predictors of economic variables such as GDP, consumers' expenditures or industrial production. The empirical literature has often investigated the extent to which confidence indicators contain information over and above economic fundamentals (INIS, 2014). In other words, can confidence measures predict economic outcomes after the appropriate macroeconomic variables, such as income, unemployment or inflation, have been taken into account? Several studies have found that forecast accuracy improves with the inclusion of survey-based indicators, although the evidence has not been unanimous (Strasser and Wohlrabe, 2015).

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. The inclusion of confidence indicators also reduced the forecasting error associated with quantitative estimates for two of the countries in their sample. Santero and Westerlund (1996) found that confidence measures 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 more useful than consumer confidence indicators for economic analysis. Kabundi (2004) found that their confidence indicator predicted economic growth in France with a relatively high degree of accuracy. Mendicino and Punzi (2013) found that shocks to forward-looking confidence indicators accounted for a sizeable fraction of variation in economic activity in Portugal.

Most studies have focused 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 in 8 countries. The results confirmed the predictive power of the consumer confidence as a leading or coincident indicator, depending on the country. Consumer confidence had a significant effect on the evolution of GDP, and led GDP independently from other macroeconomic variables. 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 of information contained in other variables, which supported the “news” view of confidence.

Leduc and Sill (2013) used confidence indicators from the Survey of Professional Forecasters, as well as the University of Michigan survey, to investigate the impact of changes in expectations on economic activity. They found that survey expectations contained important information that was relevant for understanding movements in macroeconomic variables, even after controlling for movements in forward-looking financial variables. Kilic and Cankaya (2016) analysed the effects of the consumer confidence on economic activity in the US. Their results showed that consumer confidence indicators provided information that could not be extracted from macroeconomic variables.

Other studies have found that confidence indicators can play a significant role in predicting recessions. For instance, the ECB (2013) included the EC consumer confidence index, along with the OECD leading indicator for the euro area in a probit model. This model captured business cycle phases relatively well, with probability values increasing when recessions occurred. The drawback was that the probability also increased during periods without recessions, i.e. there were some false positives.

It may be that abrupt shifts in confidence are particularly relevant to signal changes real activity (e.g. only below a certain threshold) (INIS, 2014). The 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 economic variables and do not carry information over other economic series, they may still be useful for monitoring economic developments and for real-time forecasting (nowcasting) of real economic activity. This is because they are available long before official quantitative statistics and are subject only to limited revisions (Santero and Westerlund, 1996). Most real data on the euro area, for instance, are released with a delay of at least 45 days compared to the reference month, so data referring to January is only available by mid-March. Business surveys, on the other hand, are usually available within or at the end of the reference month (e.g. the Italian survey data are released about 45 days before the industrial production index). Confidence indicators can provide valuable information on the evolution of the economy over this period, which is one of the reasons why they are popular (Parigi and Golinelli, 2004). In this sense, even if the confidence indicators are coincident indicators of real activity, the fact that they are available much earlier means that they are quasi-leading indicators.

A number of studies have demonstrated that confidence indicators are useful for nowcasting economic activity. Gayer, Girardi and Reuter (2014) evaluated the impact of new releases of financial, real and survey data (using the EC surveys) on nowcasting euro area GDP throughout each quarter. They found that survey and real data improved forecast accuracy throughout the entire sequence of nowcasts. Confidence indicators contained informational content even after controlling for timeliness, because of their broad sectoral coverage and forward-looking nature. In contrast, financial data turned out to be irrelevant predictors once they controlled for timeliness. In a similar exercise, Matheson (2007) examined the informational content of data releases on nowcasts of GDP and inflation in New Zealand. Analysing the marginal value of each type of data release revealed the importance of the business survey data in determining how model predictions evolve through each quarter. Repeating the forecasting exercise on the real-time panels without the business data led to a deterioration in forecast accuracy. The importance of business survey data to forecasting was not only due to their timeliness, but also to the underlying quality of the data. The results were consistent with the literature showing that qualitative surveys are not only timely proxies for hard data, but contain complementary information for understanding business cycle developments.

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 the two South African business confidence indicators, the BER and SACCI, 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 rather than a leading relationship. The BER indicator seemed to display stable 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.

2.3 Summary

In practice, analysts typically calculate balances to aggregate information from business and consumer surveys to construct proxies for confidence. They often calculate composite measures based on a set of questions for each sector, including questions of current conditions and forward-looking expectations. Confidence indicators have been found to be useful in some cases as leading indicators, as well as for prediction or forecasting exercises, even after controlling for other economic variables. Even in cases where the unique information content is limited, the timeliness of survey indicators may make them useful for monitoring developments and for real-time forecasting (nowcasting).

In South Africa there are only two regularly published business confidence indicators, the BER BCI and the SACCI BCI. The SACCI BCI is not a true confidence measure, and the BER BCI is a measure of current conditions, based on a single question, with survey responses weighted in an ad hoc manner. This paper aims to improve on the existing measures of confidence for South Africa, by calculating composite forward-looking indicators of business confidence, based on the BER business tendency survey microdata, which are systematically weighted, and calculated at sectoral level and in the aggregate. The confidence indicators will then be evaluated to see if they provide plausible results and if they are an improvement on the current measures.

3 Uncertainty

This section provides a brief review of the literature on uncertainty. 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).

3.1 Theoretical Links

The theoretical literature emphasises two negative and two positive channels for uncertainty to influence economic activity. 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). Because it increases the value of waiting for new information, uncertainty delays the current rate of investment (Bernanke, 1983). 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[5], 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

[5]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.

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. Thus, the initial "bust" is followed by a quick pick-up and overshoot in economic activity (Bachmann, Elstner and Sims, 2013).

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, and @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 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.

Bonciani and Roye (2015) argue 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.

3.2 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 uncertainty: how to construct proxies for uncertainty and how to distinguish a separate impact of uncertainty from recessions. 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 a broad range of factors.

3.2.1 Measuring Uncertainty

The literature has proposed a wide range of proxies for uncertainty, which can be grouped into five major categories, depending on the nature of the data used for their construction. The first category uses financial data, with the majority of studies using as proxies the implied or realised volatility in the stock market, GDP, bond yields or exchange rates. The rationale is that more volatile series are more difficult to forecast, and are associated with a greater the degree of uncertainty (Bloom, 2014). Bloom (2009), Baker and Bloom (2013), Bonciani and Roye (2015) and Leduc and Liu (2015), for instance, used stock market volatility. A popular proxy is the Chicago Board Options Exchange Market Volatility Index, which focuses on the implied volatility of the S&P 500 index. It reflects the dispersion of market participants' guesses about the future level of stock prices, as measured by the implied dispersion across all options with a given time to maturity. The most frequent criticism is that developments on stock markets may only partly reflect developments in the real economy (Girardi and Ruiter, 2015).

The second category uses new information in the construction of uncertainty indicators. The most prominent examples are proxies based on references to "uncertainty" in the media. Baker, Bloom and Davis (2015), for instance, developed economic policy uncertainty indices 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. One criticism is that the selection of search terms and newspapers entails a certain degree of subjectivity (Girardi and Ruiter, 2015).

The third category is derived from the disagreement of professional forecasters. The rationale is that a larger dispersion of opinions about the future indicate a higher degree of uncertainty. Popescu and Smets (2010), for instance, used a proxy for uncertainty based on the dispersion of professional forecasts of consumption, output, investment, industrial production, interest rates and prices in the German economy. The downside is that the factors guiding the forecasts of a limited set of professional forecasters might differ from those influencing producers and consumers (Girardi and Ruiter, 2015).

The fourth category is the dispersion of responses from business and consumer surveys. For instance, Bachmann, Elstner and Sims (2010) and Bachmann, Elstner and Sims (2013) used the dispersion of business survey responses, as well as the dispersion in individual forecast errors to construct proxies for the US and Germany. Arslan, Atabek and Timur (2011) use a similar measure of squared expectations errors to construct uncertainty indicators for Turkey. Girardi and Ruiter (2015) derived survey-based indicators in a similar vein, but with the difference that they did not require microdata, were derived from all forward-looking questions, and were available in real-time. Leduc and Liu (2015) also used a survey-based proxy for uncertainty, 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). 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 (Girardi and Ruiter, 2015).

A fifth category was introduced by Jurado, Ludvigson and Ng (2015). They argued that indicators of uncertainty should reflect the common variation across a vast array of variables, 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. They extracted common factors, used them to predict industrial production, and subsequently calculated the forecast errors. Increases in the volatility of forecast errors were interpreted as increases in uncertainty. The disadvantage is that the indicator is an *ex post* measure, which requires the actual outcome of the forecasted time series before computing the indicator (Girardi and Ruiter, 2015).

In the South African context, a few studies have constructed proxies for uncertainty. Redl (2015) 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.

Hlatshwayo and Saxegaard (2016) constructed a measure South African Economic Policy Uncertainty, by looking at "news chatter" in the press, similar to the method used in Baker, Bloom and Davis (2015). They constructed both economic policy and political uncertainty indices at aggregate level and industry-related indices at the sector level, by counting the number of articles that matched specific search algorithms. For instance, the Aggregate Economic Uncertainty was constructed by including articles containing 3 mentions of words related to policy, economics, and uncertainty (i.e., one mention of each area) within 10 words of "South Africa". The absolute counts were normalised and all indices were standardised. McClean (2015) constructed a similar news-based index for aggregate South African policy uncertainty. He found a moderate correlation between this index and the SAVI index and with SA government bond yields.

Pellissier and Fusari (2007) used the BER's manufacturing surveys to construct a measure of uncertainty. "Volatility" in survey expectations was derived from the (unweighted) percentage of survey respondents changing their expectation between survey periods. "Realization" of survey expectations was derived similarly from changes in survey expectations period $t-1$, compared to survey realisations in period t. They found a negative relationship between Volatility and Realization for survey responses relating to business conditions, production, sales, fixed investment and prices. Hart (2015) also used the BER's survey of the manufacturing sector to construct dispersion measures of uncertainty, similar to the method used in Bachmann, Elstner and Sims (2010).

Recently, NWU (2016) constructed a new Policy Uncertainty Index for South Africa. The index has three components: the frequency of references to policy-related economic uncertainty in leading publications; expert opinions drawn from a cohort of leading private sector economists; and responses from a BER survey of manufacturers on whether the political climate is a constraint to doing business. This index is only available from July 2015, but will become an invaluable gauge of policy uncertainty over time.

3.2.2 The Impact of Uncertainty

The majority of studies seem to find a significant negative relationship between proxies of uncertainty and economic activity, although this does not necessarily imply a causal relationship. To identify the impact of uncertainty on firms and consumers, the literature has taken three approaches (Bloom, 2014). The first approach uses structural models to identify the potential impact of uncertainty shocks. A second approach relies on timing, typically in a VAR framework, by estimating the movements in economic activity that follow changes in uncertainty. A third approach exploits natural experiments like disasters, political coups, or exchange rate movements.

A number of papers have used structural models (i.e. DSGE models) to investigate potential mechanisms for uncertainty to influence economic activity. Empirical VAR models are then used to confirm the theoretical model predictions. In a seminal paper, Bloom (2009) used a structural model to simulate the impact of an uncertainty shock, which produced 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, with a shock to uncertainty generating a decline and then an overshoot in employment and production.

Bloom, Bond and Van Reenen (2007) developed a model of the firm's investment decisions. With partial irreversibility, the impact on investment of a firm-level demand shock tended to be weaker for firms that were subject to a higher level of uncertainty. Their empirical model found evidence of more cautious investment behaviour for firms subject to higher uncertainty. Leduc and Liu (2015) used a structural model with search frictions and nominal rigidities to illustrate the transmission mechanism through which uncertainty could produce large macroeconomic effects. Their econometric model found that uncertainty shocks acted like aggregate demand shocks, raising unemployment and credit spreads, and lowering investment, inflation and short-term interest rates. Bonciani and Roye (2015) investigated the effects of uncertainty shocks under financial frictions within a structural model. They found that higher uncertainty reduced macroeconomic activity and showed that the impact of uncertainty shocks was potentially larger during a recession.

A number of studies have investigated the timing of the relationship between uncertainty and economic activity in a VAR framework. In general the results are similar to Bloom (2009). Arslan, Atabek and Timur (2011) found that an increase in aggregate uncertainty was followed by a significant decrease in output. Baker, Bloom and Davis (2015) investigated the effects of their Economic Policy Uncertainty measure, finding negative effects for firms heavily exposed to government contracts. At the macro level, positive innovations in uncertainty preceded declines in investment, output and employment. Girardi and Ruiter (2015) found shocks to uncertainty were quantitatively important drivers of economic fluctuations, leading to a temporary reduction in real activity. Their survey-based uncertainty indicators accounted for a much larger fraction of real GDP variability than other types of commonly used uncertainty gauges (e.g. stock market volatility). Jurado, Ludvigson and Ng (2015) found 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 negative correlations with real activity, but did not exhibit the overshooting pattern found in other studies.

Bachmann, Elstner and Sims (2010) found that innovations to their survey-based uncertainty 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. 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 shocks to uncertainty were 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, although 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. The results for the US data suggested that some of the other mechanisms proposed in the literature, such as financial frictions may be important.

A number of subsequent studies have investigated the interaction of uncertainty and financial frictions. Popescu and Smets (2010) argued that once a measure of financial stress is included in the regressions, the independent role of uncertainty shocks becomes minimal. They found that exogenous increases in uncertainty had a small and temporary contractionary effect on output, but the real effects of financial stress (financial risk premia) were much larger and more persistent. Caldara *et al.* (2016) found that uncertainty shocks had a significant negative impact on both financial conditions, as measured by an increase in the excess bond premium, and on real economic activity. Their results suggested that increases in uncertainty that were associated with a tightening of financial conditions had a particularly large negative effect on real economic activity and the stock market.

Other studies have exploited natural experiments like disasters, political coups, or exchange rate movements. For instance, Baker and Bloom (2013) used natural disasters, terrorist attacks and unexpected political shocks as instruments for the usual stock market proxies of uncertainty. They found that uncertainty shocks accounted for at least half of the variation in GDP 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. Firms affected by this exogenous increase in uncertainty decreased their planned investment (into equipment/machinery and construction), relative to firms that were unaffected. However, once they controlled for the degree of irreversibility of firm investment, the relationships were no longer significant.

There is relatively little evidence on the impact of uncertainty in South Africa. Developing countries tend to experience higher uncertainty because they 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 (Bloom, 2014). 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 analysing 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, while not undergoing the same levels of financial stress and instability as developed countries. He found an increase in uncertainty was associated with a subsequent 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.

Hlatshwayo and Saxegaard (2016) explored the role of policy uncertainty in reducing the responsiveness of exports to relative price changes, through the wait-and-see effect. They found that increased policy uncertainty reduced the responsiveness of exports to the REER and had short and long-run effects on export performance. A measure of competitiveness that adjusted for uncertainty and supply-side constraints outperformed the REER in tracking export performance.

Hart (2015) investigated the relationship between sentiment and economy activity in the South African manufacturing sector from 2001Q2 to 2014Q2. 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. 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 limited sample period. This paper will build on this approach, expanding the study to include all of the surveyed sectors for the full available period.

3.3 Summary

There has been a recent surge in research interest in uncertainty. The literature has proposed a wide range of proxies for uncertainty, which can be grouped into five major categories. All proxies for uncertainty measure a specific type of uncertainty and have their own strengths and weaknesses. The majority of studies seem to find a significant negative relationship between proxies of uncertainty and economic activity.

Only a few studies have constructed proxies for uncertainty in South Africa and none has fully exploited the information contained in the BER business tendency surveys. Survey-based measures have the advantage that they are derived from opinions of key economic agents. This paper aims to contribute to the literature by constructing composite forward-looking indicators of uncertainty for South Africa, which are systematically weighted, and calculated at sectoral level and in the aggregate. The uncertainty indicators will then be evaluated to see if they provide plausible results and whether they can provide any evidence on the impact of uncertainty in South Africa. The following section describes the BER business tendency surveys that are used to construct the sentiment measures for South Africa.

4 Data: Business Tendency Surveys

Business tendency surveys are conducted to obtain qualitative information that is useful in monitoring the current business situation and forecasting developments in the business cycle. Qualitative surveys can often be completed more easily and quickly than quantitative surveys. The results can be published much sooner than official statistics, which are often released with a significant delay by statistical agencies. Survey data have 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 implemented and will then be picked up in quantitative statistics). This is reflected in the extensive use of confidence measures as leading indicators of the business cycle (OECD, 2003).

4.1 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 European Commission business tendency surveys, the German Ifo Business Climate Survey, the Federal Reserve Bank of Philadelphia's Business Outlook Survey, and the Bank of Japan's Tankan survey (OECD, 2003).

During the last month of each quarter questionnaires are sent to 1,000 firms in each of the manufacturing and services sectors and 1,400 firms in each of the building and trade sectors (i.e. retail, wholesale and motor vehicles). The questionnaires are completed by senior executives of the firms. The business surveys contain questions, amongst others, on current and expected future developments regarding sales, orders, employment, inventories, prices and constraints. 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.

Table 1 reports the details of the survey data. The sample runs from 1992Q1 to 2015Q3, although the survey of the services sector only started in 2005. Figure 1 illustrates the number of respondents over time per sector. Around 1,000 completed questionnaires are received every quarter, leading to an overall sample size of 106,255. All of the surveys have a few missing quarters, when the microdata was lost. The overall panel sizes and response rates have remained relatively stable over time, although the response rates are relatively low by international standards (Kershoff, 2015).

Table 1: Sample Characteristics

Sector	Sample	Total Obs	Obs/Quarter	Response Rate	Missing Quarters
Manufacturing	1992Q1-2015Q3	35560	386.52	0.39	1997Q4,2000Q1,2005Q4
Construction	1993Q2-2015Q3	18733	217.83	0.16	1993Q4,1998Q3,2000Q2,2005Q4
Trade	1992Q2-2015Q3	39056	429.19	0.31	1992Q4,1993Q3,2005Q4
Services	2005Q2-2015Q3	12906	314.78	0.31	2005Q4
Total	1992Q1-2015Q3	106255	1130.37	0.24	2005Q4

The sample of firms remains relatively stable from one survey to the next, effectively creating a panel. The panel is partly fixed and partly rotating, as inactive firms that fail to respond for a period of two years are removed and replaced with new firms. Panels are useful for conducting business tendency surveys. 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 are more likely to reflect changes in the variables under consideration, rather than changes in the sample from the one survey to the next, and are less influenced by the participation or non-participation of particular firms (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. 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). Practical experience has shown that non-random samples can give acceptable results in business tendency surveys (OECD, 2003).

The BER makes no provision for firms that were not selected or did not respond during sampling. It is implicitly assumed that their responses correspond with those of the participants. This

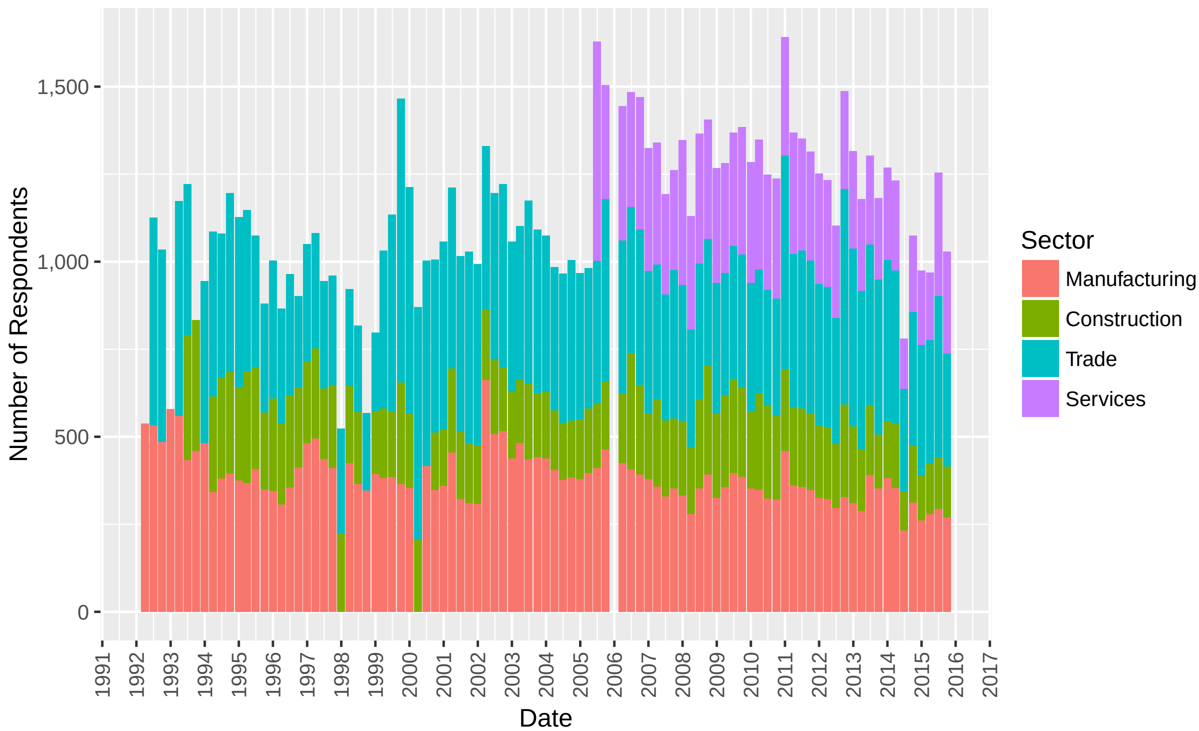

Figure 1: The number of respondents over time per sector

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 and the responses cannot vary infinitely. He found evidence for this assumption when the inclusion of latecomers had almost no effect on the volatility and tracking record of the results, even at higher levels of disaggregation.[6]

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. Results tend to remain valid even if the sample size is small and response rate relatively low. A rule of thumb is that around 30 reporting units are sufficient to obtain an acceptable level of precision for each stratum (OECD, 2003). This may be a maximum because some kinds of activity will be dominated by a few large enterprises. The reason is that the variance of the responses for ordinal-scaled data based on a stable panel sample are lower than quantitative data derived from independent surveys. The representativeness of sampling units has a smaller impact on qualitative survey results than quantitative surveys. With qualitative surveys, the purpose is to establish the majority view of the direction of change of a particular activity, rather than the size of the change. The majority view is an indication of the direction and intensity of change in the activity in question. As the majority of firms usually share the same experience, a slightly unrepresentative panel will likely produce similar

[6]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. Missing items (specific questions) and missing responses (questionnaires) are not imputed and the results are not revised to provide for questionnaires received after the results have been processed (Kershoff 2015).

results to a fully representative one (Kershoff, 2002).

The sample sizes illustrated in Figure 1 therefore seem adequate to uncover trends in the data. Kershoff (2002) found that the degree of representation of the BER's trade and building panels was adequate 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 or provinces as sub-panels. The survey responses are therefore not disaggregated further into subsectors below.

4.2 The RMB/BER Business Confidence Indicator

The BER uses these business tendency surveys to construct its business confidence indicator. The BER BCI 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 improve estimates of cyclical turning points. This is particularly useful in view of the early availability of the index. The BER index results for a particular quarter are available approximately two months before the official GDP estimates (Kershoff, 2000).

In constructing the business confidence indicator the most important issues are which survey questions to use and the weightings applied to the responses. The BER BCI is constructed from a specific question that appears in all of the surveys (Q1): *"Are prevailing business conditions: Satisfactory, Unsatisfactory?"* The business confidence index is the weighted percentage of respondents that rated prevailing business conditions as *"Satisfactory"* in a particular sector. The BER BCI reflects 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.

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). The OECD (2003) argues that answers to questions on the general business situation will usually be based on a combination of factors, such as appraisals of order books, as well as expectations about interest rates, exchange rates and political developments.

In line with the international best practice, all the survey responses are weighted (except for the building survey). Each response is multiplied by a factor, which is calculated as the product of a firm size weight and a subsector size weight (except for the motor trade, where there are no subsectors). Each firm receives a weighting in relation to turnover, or the size of workforce in the case of manufacturing.[7] The subsector size weights are based on the composition of production or sales in each subsector, as calculated by StatsSA. The BER does not apply sample weights, as it does not have access to the National Business Register and cannot calculate selection probabilities.[8]

[7]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).

[8]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 (OECD 2003).

Responses are weighted by firm size and sector weights to obtain five sectoral indices: manufacturing, building contractors (other building subsectors are disregarded), retailers, wholesalers and new vehicle dealers (used vehicles and spare parts are disregarded). The BCI is calculated as the unweighted mean of the 5 sectoral indices (services are excluded altogether).

The BER BCI is a measure of current conditions, based on a single question, with survey responses weighted in an ad hoc manner. The business surveys contain a number of questions, all of which potentially have an impact on business confidence. A composite indicator can be calculated by combining the responses to a number of questions, which is often used internationally (ECB, 2013). Moreover, the BER BCI reflects confidence in current conditions (activity) rather than forward-looking confidence. As the surveys contain questions on expectations, forward-looking responses could also potentially provide valuable information. This paper aims to build on the BER BCI by calculating composite forward-looking indicators of business confidence, which are systematically weighted, and calculated at sectoral level and in the aggregate. In addition, the BER business tendency surveys are uniquely suited to obtain measures of uncertainty to This paper aims to also construct composite forward-looking indicators of uncertainty, which are systematically weighted, and calculated at sectoral level and in the aggregate. The following section sets out the methodology for constructing these sentiment indicators.

5 Methodology

This section sets out the methodology for calculating the sentiment indicators based on the microdata from the BER business tendency surveys. These indicators of sentiment are usually constructed from the first and second moments of responses to business tendency survey questions. Survey-based measures have the advantage that they are derived from opinions of key economic agents.

5.1 Confidence

The BER business surveys contain a number of questions which may be useful in gauging business sentiment in South Africa. These include questions on general business conditions, production, orders placed, employment, and profitability. Most international institutions calculate composite indicators by combining the responses to a number of questions (ECB, 2013). Composite indicators have the capacity to react to various sources of economic fluctuations, while being resilient to fluctuations affecting single components. They may therefore exhibit fewer false alarms and fewer missed turning points than indicators based on single questions.

This paper therefore combines the responses to a number of questions to calculate composite indicators. For consistency, the composite indicators are derived from questions that are present in most of the sectoral business surveys. Table 2 reports the questions included in each of the sectoral surveys. These questions cover 6 types of variables, namely business conditions, activity (production or sales),[9] orders placed, employment, and profitability. Not all of the variables are covered in all the surveys.

[9] The wording of the questions are adopted to the characteristics of each sector (Kershoff 2015). Activity is referred to as the "volume of production" in the manufacturing survey, "the volume of building activity" in the building survey, "the volume of sales" in the trade surveys, and "the volume of business" in the services survey.

Table 2: Survey Questions used by Sector

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

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 $k > 0$. Forward-looking indicators could provide even better leading indicator properties than indicators based on current conditions. 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 $k > 0$. This paper makes a distinction between indicators of current conditions (activity) and for forward-looking conditions (confidence).

The BER business tendency surveys make this distinction possible by asking for separate responses relating to current conditions and expected future developments. The questions focused on current developments all have the follow format (e.g. Q2A): *"[Estimated development in current quarter] Compared with the same quarter of a year ago, are General Business Conditions: Better, the Same, or Poorer?"* In other words, it asks whether the factor under consideration in time t is better, the same, or poorer, compared to $t-4$. The forward-looking questions all have the following format (e.g. 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 the factor under consideration in time $t+1$ is expected to be better, the same, or poorer, compared to $t-3$. 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.[10]

[10] 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.

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). 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. Thus, activity may be defined as: $Activity_t = Frac_t(Up) - Frac_t(Down)$. Forward-looking confidence relates to firms' expectations: $Confidence_t = Frac_{t+1}(Up) - Frac_{t+1}(Down)$.

This paper calculates composite activity and confidence measures for each of the surveyed sectors. For each question, the responses are weighted by firm size and subsector weight, and balances are calculated. The composite sectoral indicators are calculated as the average of the weighted balances for the questions for each sector, as reported in Table 2. The activity measures also include the question (Q1) on business satisfaction used to calculate the BER BCI. Following the advice of the INIS (2014), the sectoral indicators are then weighted by GDP share to form the overall aggregate composite indicators.

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 (OECD, 2003). Indeed, 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 very similar, suggesting that the specific weighting adopted does not significantly alter the results. This confirms the results found by Kershoff (2015), 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 response patterns (to handle non-responses); the application of the OECD's two-step weighting procedure; the inclusion of latecomers to increase the number of responses; the use of different sector size weights for export variables; and the combination of a number of subsectors to produce a higher level of aggregation. The findings showed that the results were not sensitive to the alternative methods of aggregation.

5.2 Uncertainty

There are relatively few proxies for macroeconomic uncertainty in South Africa. None of the proxies have fully exploited the information contained in the BER business tendency surveys. This section follows Bachmann, Elstner and Sims (2010) and Bachmann, Elstner and Sims (2013) by calculating two composite forward-looking indicators of uncertainty: the cross-sectional dispersion of forward-looking responses and the cross-sectional dispersion in individual firm expectation errors. These measures are based on *ex ante* disagreement and *ex post* forecast error variance and both capture a low level of predictability. The BER survey microdata is particularly useful in this case because it allows the calculation of individual firm expectation errors, which is theoretically the stronger proxy for uncertainty.

The first measure of uncertainty is the cross-sectional dispersion of forward-looking responses, using the same set of forward-looking survey questions for each sector as reported in Table 2. For example (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?"* If the standard quantification method for survey data is used, the uncertainty measures are the cross-sectional standard deviation of responses:

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

, where Frac(Up) is again defined as the weighted fraction of firms in the cross section responding with "better" at time t.

Bachmann, Elstner and Sims (2010) and Bachmann, Elstner and Sims (2013) noted that there are two potential problems with simple dispersion as a proxy for uncertainty. 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.[11] Second, time variation in the dispersion of expectations might simply reflect time variation in the heterogeneity of expectations, without subjective uncertainty changing over time.

Accordingly, Girardi and Ruiter (2015) suggest scaling the forecast dispersion measures in period t by the dispersion of questions on current conditions in period $t+1$. The idea is that respondents' assessments of current developments should be free of any uncertainty. Accordingly, the dispersion of an "activity" question does not measure uncertainty, but the degree to which economic developments objectively differ across respondents. The dispersion of forward-looking questions reflects both the "natural" degree of dispersion and uncertainty about the future. This proxy provides a measure of the extent of uncertainty, expressed as a share of the "natural" dispersion. The uncertainty-induced change in dispersion is calculated as:

$$Dispersion_t = ln(\frac{Disp_t^{forward}}{Disp_{t+1}^{current}})$$

Bachmann, Elstner and Sims (2010) and Bachmann, Elstner and Sims (2013) recommended a qualitative index of the *ex post* forecast error standard deviation, which requires access to the microdata. 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 the *ex post* forecast errors. Pairs of questions are used to construct the forecast errors for each respondent, by comparing the expectations in period t for a specific question to the realisations for that question in period $t+1$. For instance, the survey response to Q2P in period t used to extract the expectations of general business conditions in time $t+1$ relative to $t-3$. The errors are then calculated by subtracting these expectations from the realisations from the responses to Q2A 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 3 illustrates the 9 possible expectation errors that arise.

Uncertainty is then measured as the cross-sectional standard deviation of the expectation errors in each quarter. 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

[11]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 finding of 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.

Table 3: Possible Expectation Errors

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

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.

One implication of this uncertainty indicator is that when all the firms make the same expectation error it implies no uncertainty. Arslan, Atabek and Timur (2011) argued that firms make expectation errors because of uncertainty in the economy and that expectation errors should therefore be treated as uncertainty. They call the measure used in Bachmann, Elstner and Sims (2010) and Bachmann, Elstner and Sims (2013) "idiosyncratic" uncertainty. It measures how individual firms depart from the overall mean on expectation errors. In addition, they suggest "aggregate" uncertainty, which is defined as the square of the average expectation errors made across firms. Consequently, aggregate uncertainty increases if more firms make similar expectation errors. This is akin to the measures based on the mean of the absolute expectations errors proposed in Bachmann, Elstner and Sims (2013), which one would expect to be larger in a more uncertain environment.

More formally, the uncertainty measures can be defined as:

$$\begin{aligned}
Idiosyncratic_t &= \sum_{i=1}^{n}(W_{i,t} - \overline{W}_t)^2/N \\
Aggregate_t &= \overline{W}_t^2 \\
Total_t &= \sum_{i=1}^{n}(W_{i,t})^2/N \\
Total_t &= Aggregate_t + Idiosyncratic_t
\end{aligned}$$

where $W_{i,t}$ is the expectation error of firm i at time t as introduced in Table 3, and $\overline{W}_t$ is the mean value of expectations errors.

If more firms make the same expectation errors, aggregate uncertainty will increase. If the same proportion of firms make positive and negative expectation errors, aggregate uncertainty will take a value of zero. This would imply an environment where firms face only idiosyncratic shocks. Arslan, Atabek and Timur (2011) found that idiosyncratic uncertainty did not capture economic downturns, while aggregate uncertainty seemed to be a good leading indicator for the economic activity, with large spikes in aggregate uncertainty being followed by troughs in the economic activity.

To calculate the indicators for a specific question the weightings are applied in the same way as for the confidence indicators, i.e. firm size and subsector weights. Jurado, Ludvigson and Ng (2015) argued that uncertainty manifests itself in a vast array of variables. Composite uncertainty indicators are therefore calculated as the average of a number of survey questions, as reported in Table 2. This should reduce their likelihood of producing "false positives", i.e. signalling high uncertainty where there is none, and "false negatives", i.e. failure to detect mounting uncertainty (Girardi and Ruiter, 2015). The sectoral indicators are then aggregated with GDP shares as weights to form the overall uncertainty indicators. The cross-sectional dispersion method can be seen as akin to the forecaster disagreement proxy for uncertainty used by Baker and Bloom (2013).

6 Results: Confidence

This section uses the quarterly BER business tendency surveys and the methodology described above to calculate indicators of business confidence in South Africa. Simple linear interpolation is used for the missing quarters throughout. The composite sectoral and aggregate indicators for confidence are first presented. The indicators are then compared to existing measures of confidence and related to economic activity in South Africa.

6.1 Confidence

Figure 2 illustrates the weighted sectoral Activity and Confidence indicators. The indicators seem to capture cyclical movement in the sectors. The confidence indicators seem to lead the activity indicators in each of the sectors, with turning points generally before the activity measures. This is what one would expect, given that the confidence indicators are based on forward-looking questions.

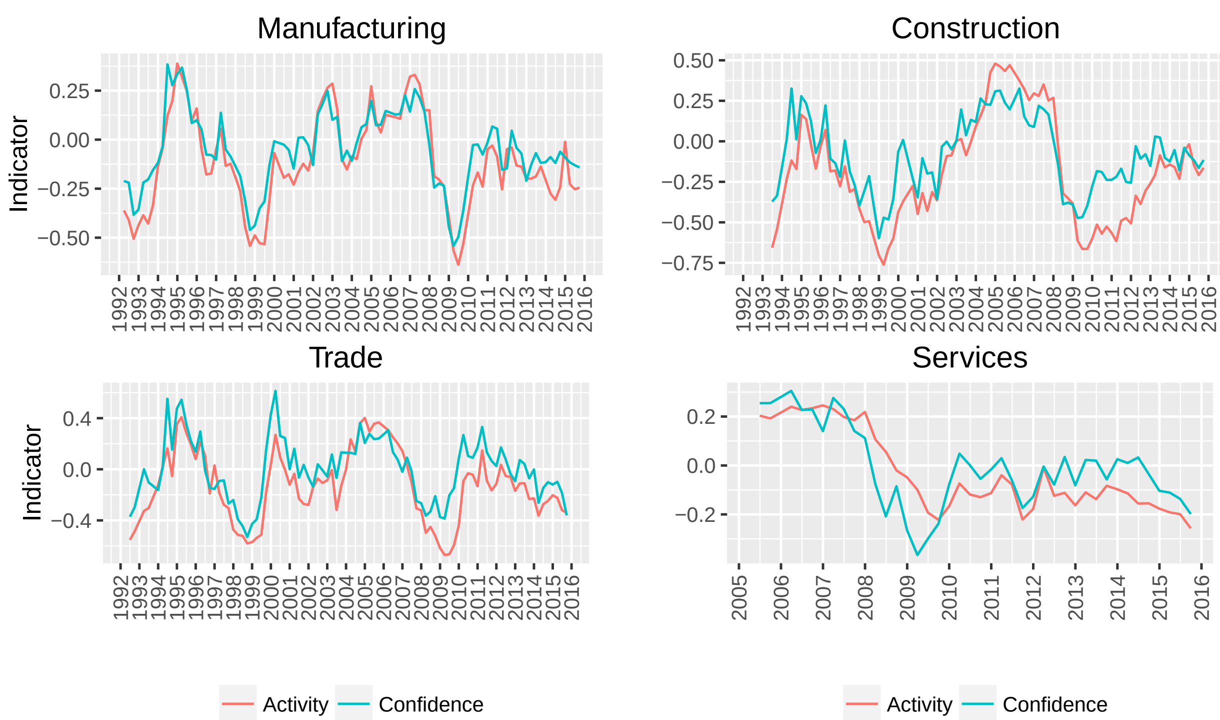

Figure 2: Weighted Sectoral Activity and Confidence Indicators

Figure 3 illustrates the weighted aggregate Activity and Confidence indicators. The shaded areas denote the recessionary periods according to the official turning points of the SARB. The indices follow a similar cyclical trend over the period and are very highly correlated, as reported in Table 4 below. The Confidence index seems to lead changes in the Activity index to some extent. The indicators appear to match the different phases of the business cycle relatively well. Turning points were generally before the official turning points, as discussed in more detail below.

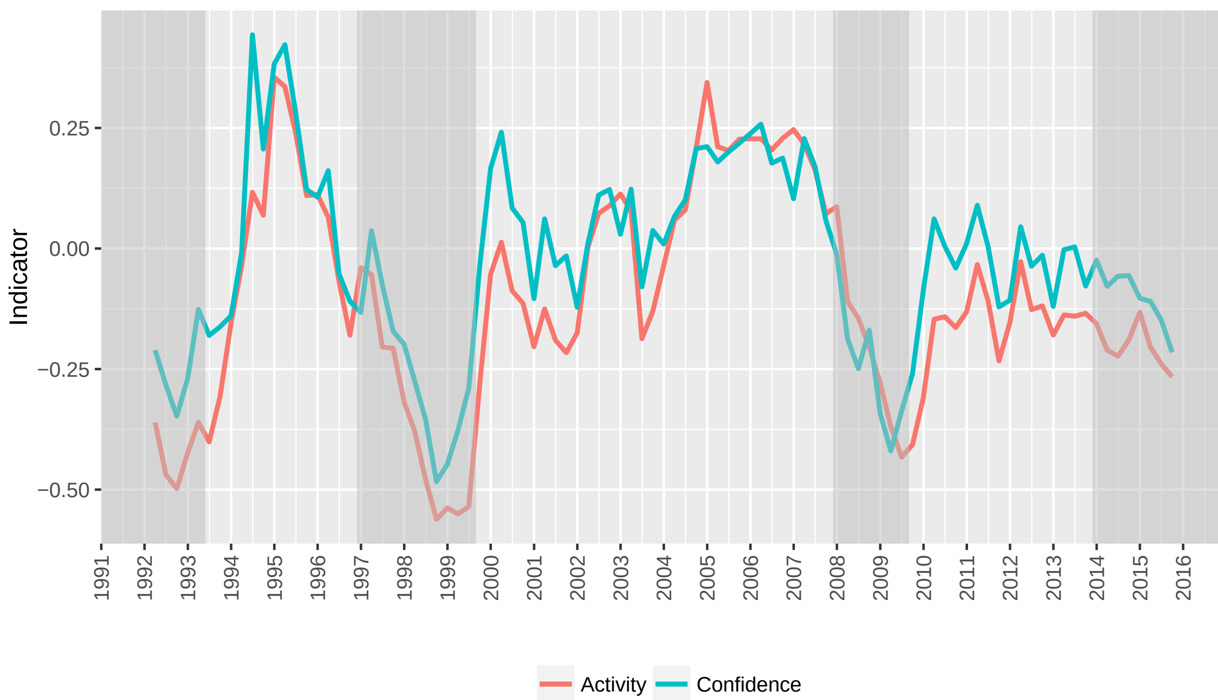

Figure 3: Weighted Activity and Confidence Indicators

The survey-based indicators appear to be plausible and potentially useful indicators of business confidence in South Africa. The following section tests for this more formally be comparing them to the existing measures of confidence and GDP growth. The unweighted versions of the indicators, calculated by stacking all of the available responses from all the surveys (i.e. completely unweighted), are very similar but slightly less volatile than the weighted versions. The specific weighting adopted therefore turns out to have very little impact on the confidence indices, implying that the specific weighting approach does not significantly alter the results. The same is true of the respective sectoral indices.

6.2 Comparison and Evaluation

This section compares the characteristics of the Activity and Confidence indicators to the two existing South African business confidence indices, the BER BCI and the SACCI BCI. All of the aggregate and sectoral confidence indicators are then related to movements in real output growth. Correlations are used to analyse the tracking record of the indicators with respect to their reference series (i.e. real GDP growth). The relationship between turning points is reported, to indicate their usefulness in terms of leading or coincident indicators. Granger causality tests are used to illuminate the timing of the relationships between the indicators and real output growth. Simple bivariate VARs are then estimated to provide some preliminary evidence on the dynamic effects of confidence shocks on the economy.

6.2.1 Correlations

Figure 4 compares the Activity and Confidence indicators to the BER and SACCI BCIs, as well as real GDP growth. Real GDP growth is measured as annual quarter-on-quarter growth, e.g. 2015Q1 over 2014Q1, which corresponds to the reference period in the BER surveys. Recessionary periods are shaded and the indicators are standardised for plotting. The confidence indicators appear to strongly pro-cyclical, and follow real GDP growth closely.

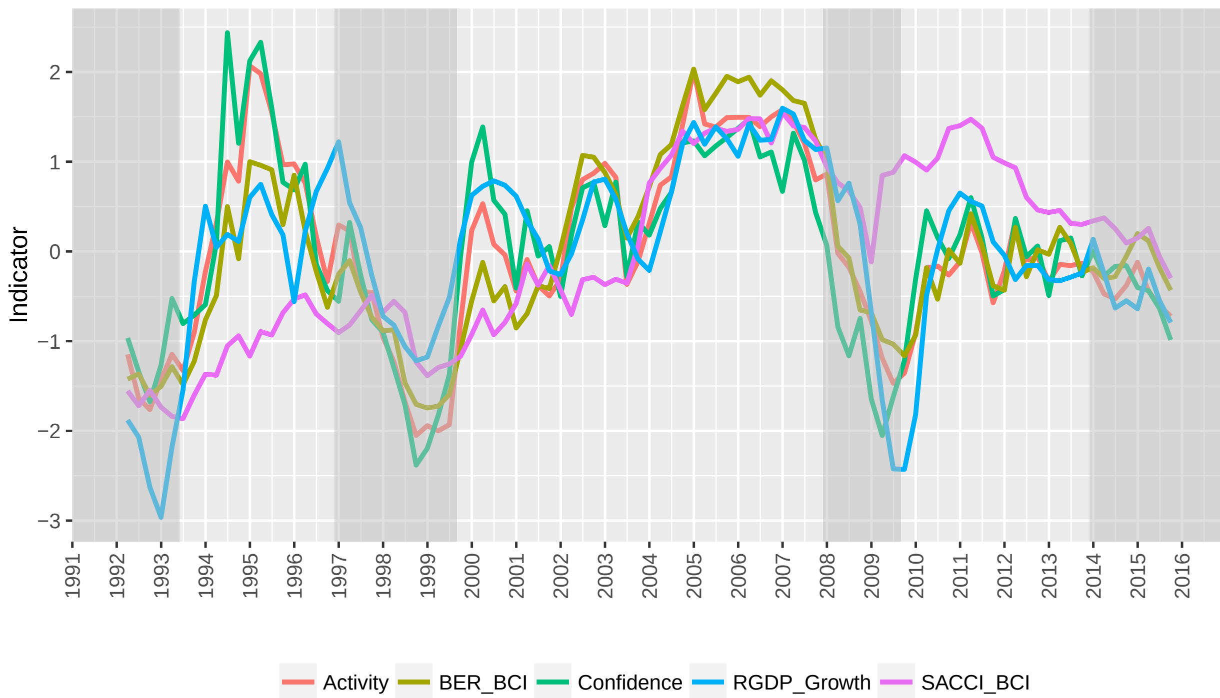

Figure 4: Weighted Indicators compared the BER BCI and SACCI BCI

The tracking record of the indicators is measured by their correlation with the corresponding quantitative reference series. Table 4 reports the contemporaneous correlations of the indicators and real GDP growth. All the indicators exhibit a significant positive correlation with real GDP growth. The Activity indicator has a higher contemporaneous correlation with real GDP growth than the BER or SACCI BCIs, which are also based on current conditions. One would expect indicators of current conditions to have a better tracking record than indicators of forward-looking expectations, although the correlation of the Confidence indicator is still relatively high (especially compared to the SACCI BCI).

Table 4: Correlations in Levels

	Activity	Confidence	BER_BCI	SACCI_BCI
Activity				
Confidence	0.91***			
BER_BCI	0.93***	0.79***		
SACCI_BCI	0.43***	0.30***	0.62***	
RGDP_Growth	0.80***	0.69***	0.75***	0.43***

Cross-correlations can be used to illustrate the dynamic relationships between the indicators and real GDP growth. Figure 5 illustrates the cross-correlograms for the indicators and real GDP growth. The Confidence measure leads the other indicators and GDP growth. The highest correlation coefficient for the Confidence measure occurs at 1 lag, with a correlation of 0.7, whereas for the indicators of activity it occurs contemporaneously. All three survey-based measures exhibit relatively high correlations with lagged GDP growth. This implies that they are all potentially useful leading indicators of real activity.

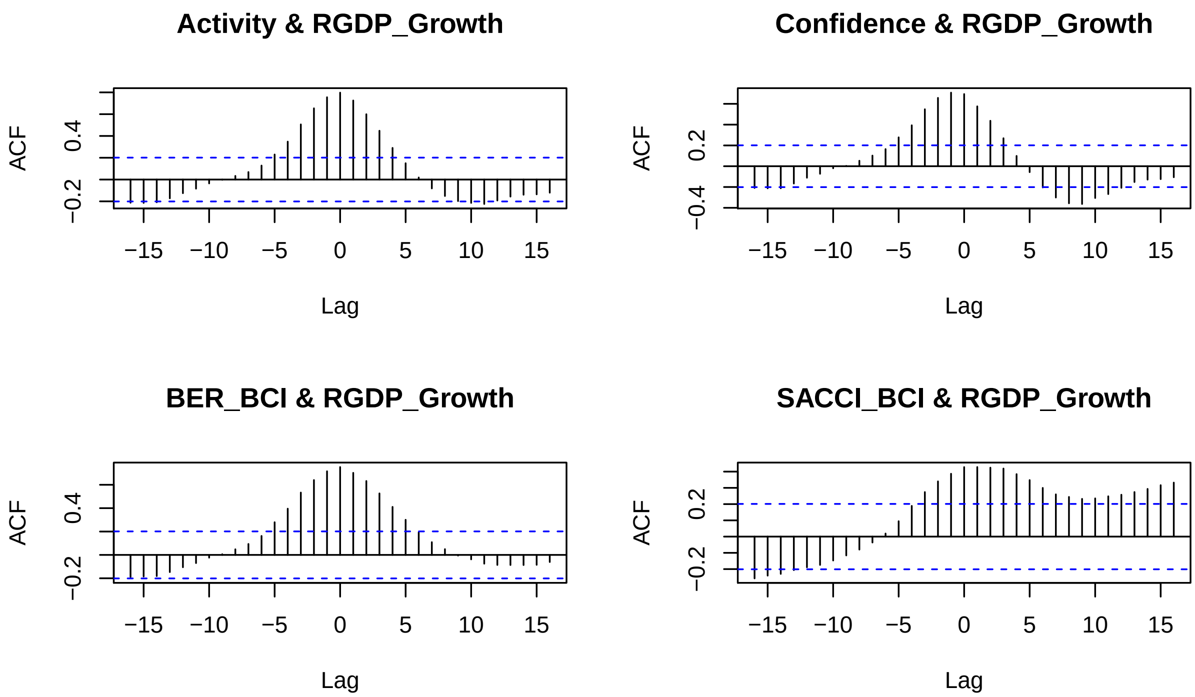

Figure 5: Cross-correlograms of confidence indicators and real GDP growth

Although there are too few cycles over the sample period to analyse cyclical turning points in full detail, it is still of interest to assess whether the indicators behave in a systematic way around cyclical turning points. In other words, do they systematically lead, coincide with, or lag peaks and troughs of the business cycle.

The turning points in the indicators are determined with the BBQ algorithm developed by Harding and Pagan (2002). The algorithm identifies local minima (troughs) and maxima (peaks) in a single time series. Censoring rules in the algorithm ensure that phases and cycles have a minimum duration. Harding and Pagan (2002) suggested a censoring rule based on a minimum of 2 quarters for each phase and 5 quarters for a full cycle. Because the indicators are quite volatile, however, this default censoring rule produces a number of very short phases (2 quarters) during the middle part of the sample period (2000-2005). The minimum was therefore increased to 3 quarters for a phase and 6 quarters for a full cycle.

The resulting turning points are reported in Table 5, along with the official reference turning points. The sample period includes 3 upswing phases and 4 recessionary periods. In addition, in 2001 and 2003 the SARB indicators pointed to possible reference turning points. Although the SARB dating committee decided at the time that neither of these periods qualified, subsequent data revisions have shown that in hindsight there could have been official peaks, especially in 2003, if the dating procedure had been followed mechanically (Venter, 2005).

The BBQ algorithm identified 5 cycles in the Activity indicator and 4 cycles in the Confidence indicator over the period. Three of these correspond to the official business cycle, while an additional shorter cycle (or false positive) occurred around the ambiguous period of 2000-2003. The survey-based indicators exhibited troughs before the 3 official trough dates, between 1 and 4 quarters before they occurred. The indicators exhibited peaks long before the official peak dates, in some cases as much as 12 quarters before they occurred. The turning points in the BER and SACCI BCI were similar to those for the Activity and Confidence indicators, although there were even more cycles in the BER BCI, especially towards the end of the sample period. The indicators therefore provided advanced warning of turning points, albeit long before the official peaks. The false positives are problematic for the use of the indicators as early warning signals. However, the reference series, real GDP growth, exhibited even more cycles when dated with the BBQ method. Its cycles corresponded more closely with those of the indicators.

Table 5: Turning Points

SARB		Activity		Confidence		BER	BCI	SACCI	BCI	RGDP	Growth
Peaks	Troughs	Peaks	Troughs	Peaks	Troughs	Peaks	Troughs	Peaks	Troughs	Peaks	Troughs
	1993Q2		1992Q3		1992Q3		1992Q3	1992Q3	1993Q2		1992Q4
1996Q4	1999Q3	1994Q4	1998Q3	1994Q2	1998Q3	1994Q4	1998Q4	1996Q1	1996Q4	1995Q1	1995Q4
2007Q4	2009Q3	2000Q1	2001Q3	2000Q1	2001Q4	2000Q1	2000Q4	1997Q3	1998Q4	1996Q4	1998Q3
2013Q4		2004Q4	2009Q2	2006Q1	2009Q1	2002Q2	2003Q2	2001Q1	2002Q1	2000Q2	2001Q4
		2012Q1	2012Q4	2011Q1		2004Q4	2009Q3	2006Q4	2008Q4	2002Q4	2003Q4
		2013Q3				2011Q1	2011Q4	2011Q1		2004Q4	2005Q4
						2013Q1	2014Q1			2006Q4	2009Q3
						2014Q4				2010Q4	2013Q1
										2013Q4	

Figure 6 compares the sectoral Activity and Confidence indicators to the BER sectoral indicators,[12] as well as the corresponding real sectoral GDP growth rates. The indicators seem to capture cyclical movements in real output over the period. Table 6 reports the contemporaneous correlations of the sectoral indicators and their respective sectoral real GDP growth rates. All the indicators are highly positively correlated with real GDP growth rates. For the manufacturing sector, the Confidence indicator exhibits the highest contemporaneous correlation. For the construction sector, the BER BCI has the highest correlation, which is interesting, as their measure includes only building contractors. For the trade and services sectors, the Activity indicators exhibit the highest correlations.

Table 6: Correlations in Levels

	Manufacturing			Construction		
Activity	Activity	Confidence	BER_BCI	Activity	Confidence	BER_BCI
Confidence	0.93***			0.89***		
BER_BCI	0.94***	0.85***		0.94***	0.76***	
RGDP_Growth	0.67***	0.68***	0.61***	0.69***	0.51***	0.77***

	Trade			Services		
Activity	Activity	Confidence	BER_BCI	Activity	Confidence	BER_BCI
Confidence	0.86***			0.78***		
BER_BCI	0.79***	0.61***				
RGDP_Growth	0.68***	0.61***	0.56***	0.85***	0.60***	

[12] The BER does not publish a confidence indicator for the services sector.

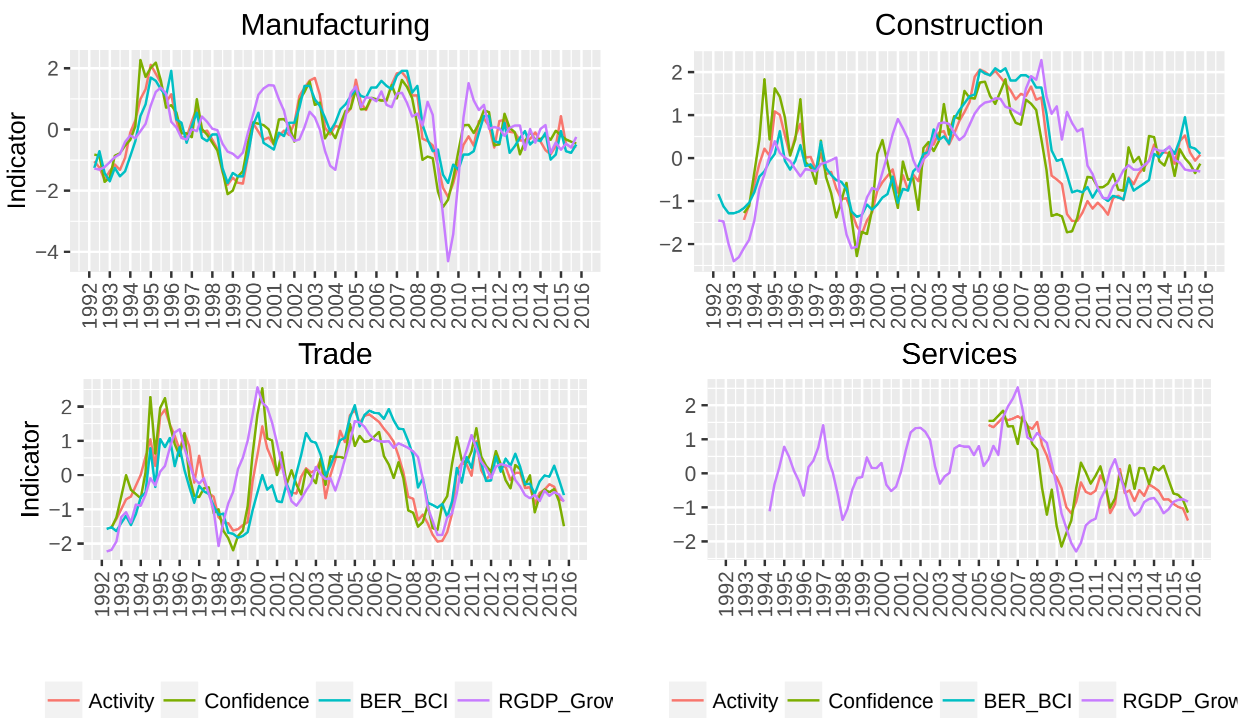

Figure 6: Weighted Sectoral Activity and Confidence Indicators

Figure 7 illustrates the cross-correlograms for the Manufacturing indicators and real GDP growth in the Manufacturing sector. The results are fairly similar to the aggregate results. Again, all three survey-based measures exhibit relatively high correlations with lagged GDP growth and the Confidence measure seems to lead the other indicators and real GDP growth. The cross-correlograms for the other sectors are very similar, except in the Services sector, where the Confidence measure has even longer leading relationship with real GDP growth.

6.2.2 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. Rejecting the hypothesis that a sentiment indicator does not Granger-cause an economic variable implies that past values of the sentiment indicator provide significant information in the estimation of the economic variable in addition to that contained in the variable's own history.

Table 7 reports the results for Granger causality tests for the confidence indicators and real GDP growth. The results suggest that the lagged values of all three survey-based confidence indicators significantly predict real GDP growth, with limited evidence of Granger-causality in the reverse direction. In other words, the results suggest that all three survey-based confidence indicators contain relevant information for the prediction of output growth. This implies that the survey-based

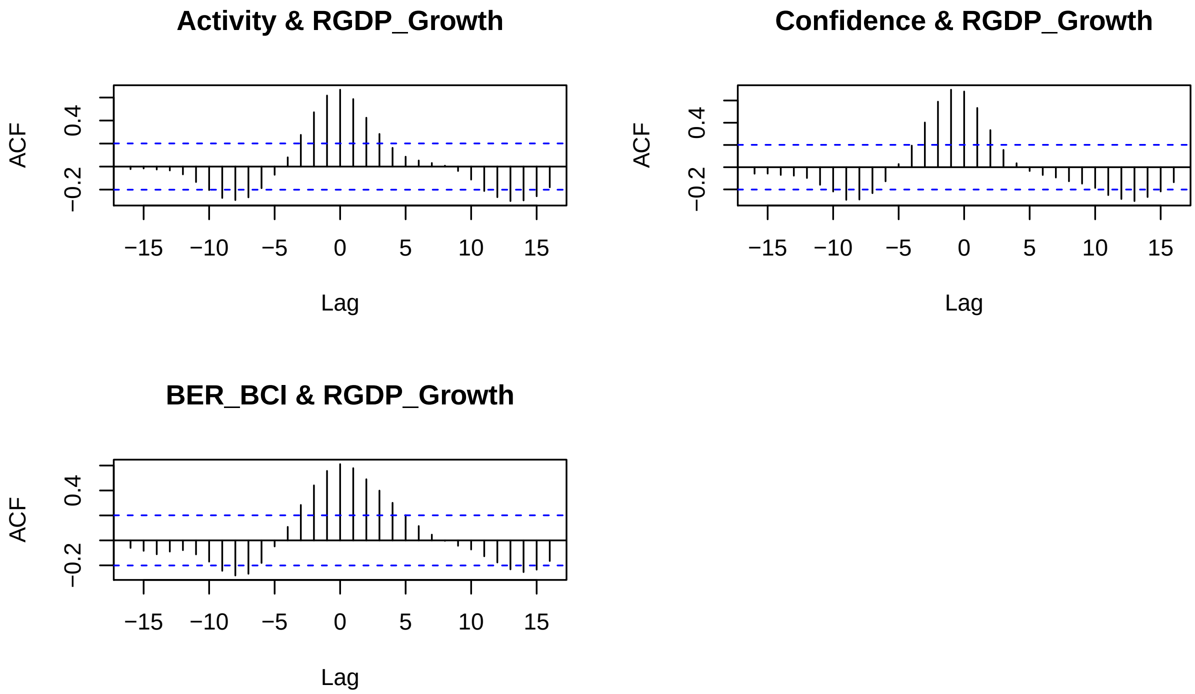

Figure 7: Cross-correlograms of Manufacturing indicators and real GDP growth

measures exhibit a leading relationship with real GDP growth. Pellissier (2002) used Granger causality tests to investigate the relationship between the BER BCI and the SARB's coincident business cycle indicator. He argued that a high level of feedback between business confidence and real GDP growth indicated a coincident rather than a leading relationship. However, even in that case, survey-based business confidence exhibit quasi-leading indicator attributes in terms of its timely availability and the finality of its data.

Table 7: Granger causality tests

Granger causality H0:	statistic	p-value
Activity do not Granger-cause RGDP_Growth	3.44**	0.03
RGDP_Growth do not Granger-cause Activity	1.596	0.21
Confidence do not Granger-cause RGDP_Growth	4.238**	0.02
RGDP_Growth do not Granger-cause Confidence	0.788	0.46
BER_BCI do not Granger-cause RGDP_Growth	4.032**	0.02
RGDP_Growth do not Granger-cause BER_BCI	1.216	0.30
SACCI_BCI do not Granger-cause RGDP_Growth	0.647	0.52
RGDP_Growth do not Granger-cause SACCI_BCI	0.309	0.73

Table 8 reports the results of the Granger causality tests for the sectoral indicators and their corresponding real sectoral GDP growth rates. The results are similar to those for the aggregate indicators, except for the trade sector (i.e. wholesale, retail and motor vehicles), where lagged values of real GDP growth significantly predicts all three survey-based confidence indicators. This implies that the confidence indicators for the trade sector are lagging indicators for real GDP growth in that sector.

Table 8: Granger causality tests

Granger causality H0:	Manufacturing	Construction	Trade	Services
Activity do not Granger-cause RGDP_Growth	3.953**	7.503***	1.829	4.245**
RGDP_Growth do not Granger-cause Activity	2.749*	1.183	4.484**	0.916
Confidence do not Granger-cause RGDP_Growth	6.929***	6.419**	0.862	8.62***
RGDP_Growth do not Granger-cause Confidence	2.509*	0.025	6.034***	0.093
BER_BCI do not Granger-cause RGDP_Growth	3.872**	6.075**	0.412	
RGDP_Growth do not Granger-cause BER_BCI	2.476*	0.017	2.513*	

6.2.3 VAR Analysis

This section provides some preliminary evidence on the dynamic effects of confidence shocks on real economic activity. 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 section follows the literature (e.g. Taylor and McNabb (2007) and Barsky and Sims (2012)) in using standard recursive VARs to trace out the dynamic responses of economic activity to surprise increases in confidence. The aim is to investigate whether these measures have a significant dynamic relationship with real output, and whether a shock to confidence generates responses which are in line with the theory.

The relationships are investigated for the aggregate variables, as well as for each sector separately, using bivariate recursive VARs featuring a measure of confidence and real GDP growth. A bivariate system is a parsimonious way to model the joint dynamics of sentiment and real economic activity (Bachmann, Elstner and Sims, 2013). 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 output, z is confidence, and ϵ is the residual of each equation.

A range of VARs are estimated on the quarterly data running from 1992Q1 to 2015Q3. The confidence indicators enter in levels, while the activity variables enter as annual quarter-on-quarter growth rates, which corresponds to the survey reference period. Unit root test indicate that virtually all of the aggregate and sectoral Activity and Confidence indicators and the corresponding real GDP growth rates are stationary, the exception being real GDP growth in the services sector, probably due to the shorter sample period. The appropriate number of lags are selected by means of the Akaike information criterion (AIC), the Schwarz criterion (SC) and the Hannan-Quinn criterion (HQ). The most parsimonious model is selected, provided that the diagnostic tests (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.

The sentiment indicators are ordered first in a recursive identification strategy, with the Cholesky decomposition used to identify structural shocks. With this ordering, shocks to confidence are allowed to have a contemporaneous impact on activity, but shocks to activity have no contemporaneous impact on confidence ($\beta_{21} = 0$). In other words, innovations to the confidence indicators influence economic activity on impact, but not vice versa. This is the identification strategy and ordering used in the literature (e.g. Leduc and Sill (2013), Mendicino and Punzi (2013), and Bachmann, Elstner and Sims (2013)). It can be motivated by the timing of the surveys: when the survey is completed in time t the respondents do not know the realisations of output growth in time t, as the response deadline is generally the second month of the quarter.

This allows for the generation of impulse response functions (IRFs), which show the dynamic impact of a shock to confidence on the system. The shock itself is an innovation to the residual in the equation of the variable of interest. Figure 8 illustrates the IRFs of a bivariate VARs for the Activity indicator and real GDP growth. The left panel plots the responses of real GDP growth to an orthogonal shock in the indicator, with 95% bootstrap confidence intervals. Following an increase in confidence, real GDP growth increases by around 0.3% on impact, with a peak at 3 quarters. The impact 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)). The right panel plots the response of Activity to an orthogonal shock in real GDP growth. Following an increase in real GDP growth, there is an insignificant increase in Activity of around 2% after two quarters. The results are similar for alternative orderings. The results are virtually identical for the Confidence indicator and the BER BCI, whereas the SACCI BCI does not exhibit a significant relationship with real activity.

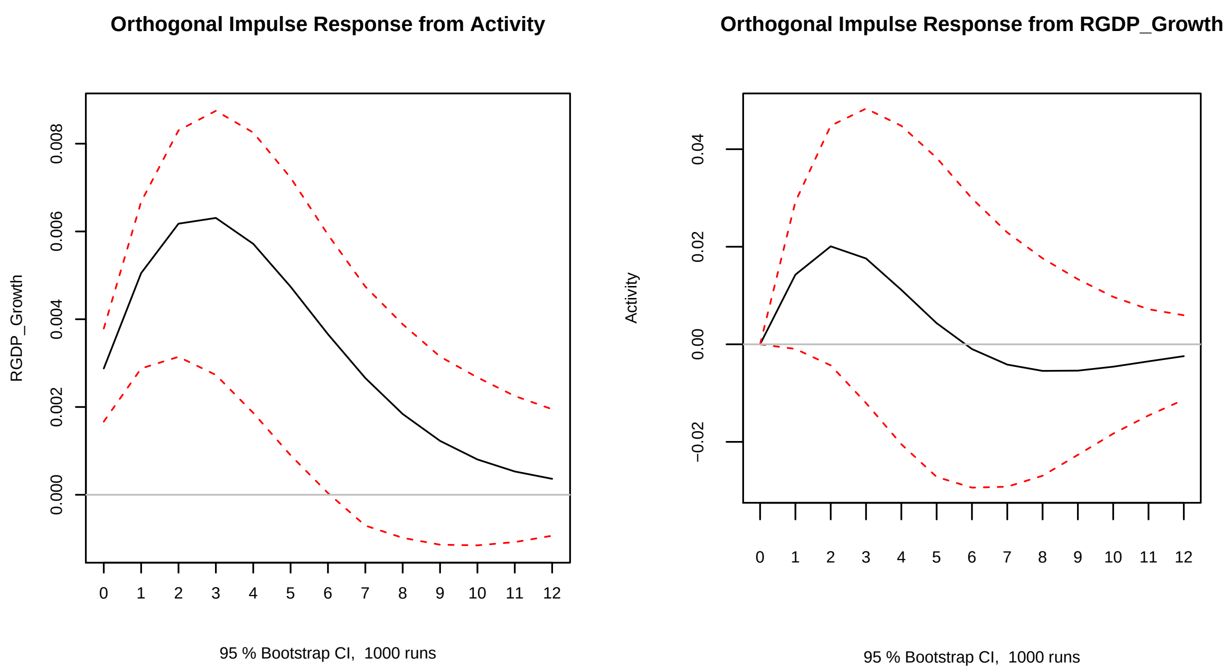

Figure 8: IRFs of Activity and real GDP growth

The importance of innovations can also be examined with variance decompositions. While the IRFs describe the reaction of a variable of interest to an exogenous shock, the decomposition of the forecast error variance of a given variable shows how much of the error can be explained by exogenous shocks to the other variables in the system (Girardi and Ruiter, 2015). The forecast error variance decomposition (FEVD) tells us the proportion of the movements in a sequence due to its own shocks and shocks to the other variable. Figure 9 illustrates the FEVDs for the Activity indicator and real GDP growth. Up to around half (52%) of the movements in real GDP growth are explained by the confidence indicator over the longer term, while real GDP explains up to 3% of the variance in the Activity indicator.

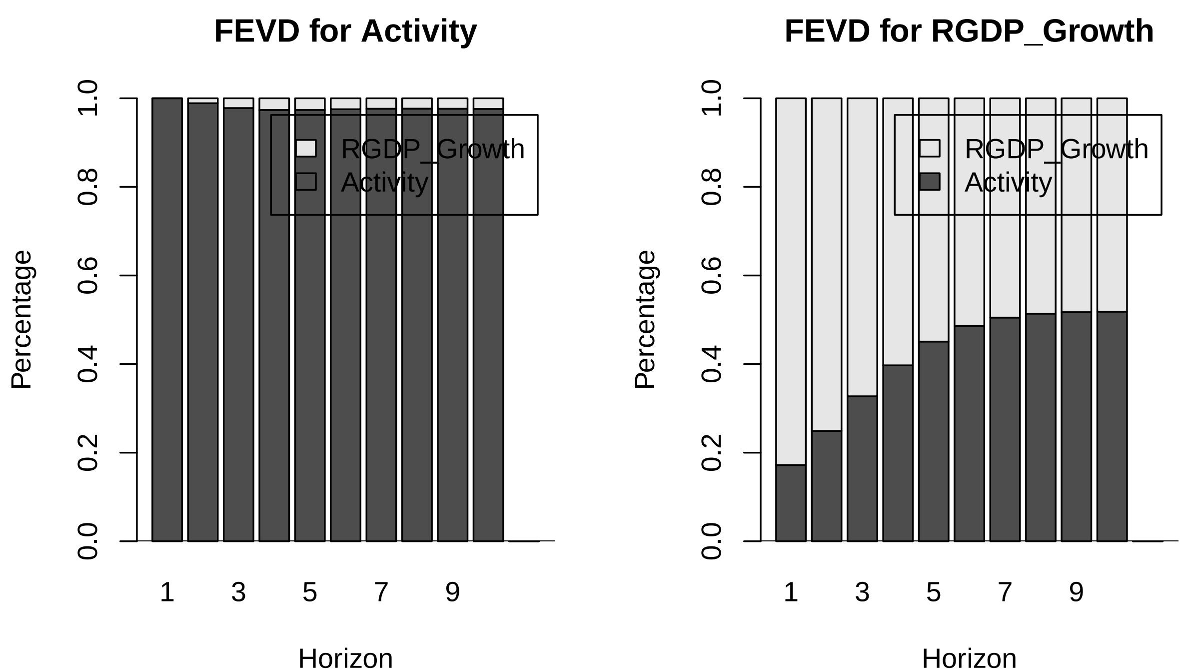

Figure 9: FEVDs of Activity and real GDP growth

The results for the sectoral indicators are very similar to the aggregate results. Figure 10 illustrates the IRFs of a bivariate VARs for the Manufacturing Activity indicator and real GDP growth in the Manufacturing sector. Following an increase in confidence, real GDP growth increases by around 1.5% on impact, with a peak at 2 quarters. The impact on the growth rate dies out after approximately 4 quarters. Following an increase in real GDP growth, there is a significant increase in Activity of around 2% in the following quarter. The results are similar for alternative orderings. The results for the other sectoral indicators are very similar to those for the Manufacturing sector, with the exception that in the Construction sector the impact of a shock to Activity on GDP growth does not die out within the forecast horizon of 12 quarters.

Figure 11 illustrates the FEVDs for the Activity indicator and real GDP growth in the Manufacturing sector. Up to more than a third (39%) of the movements in real GDP growth are explained by Activity over the longer term, while real GDP explains up to 2% of the variance in Activity. Overall, the results suggest that shocks to confidence are important for economic fluctuations, accounting for between around 20% and 60% of the forecast error variance of the real GDP growth rate, depending on the level of aggregation and the indicator used.

6.2.4 Summary and Suggested Further Analysis

All the indicators of confidence examined in this section exhibit a significant positive correlation with real GDP growth. The Activity indicators generally exhibited the highest correlation with real GDP growth and therefore the most successful tracking record. The Confidence indicators generally lead

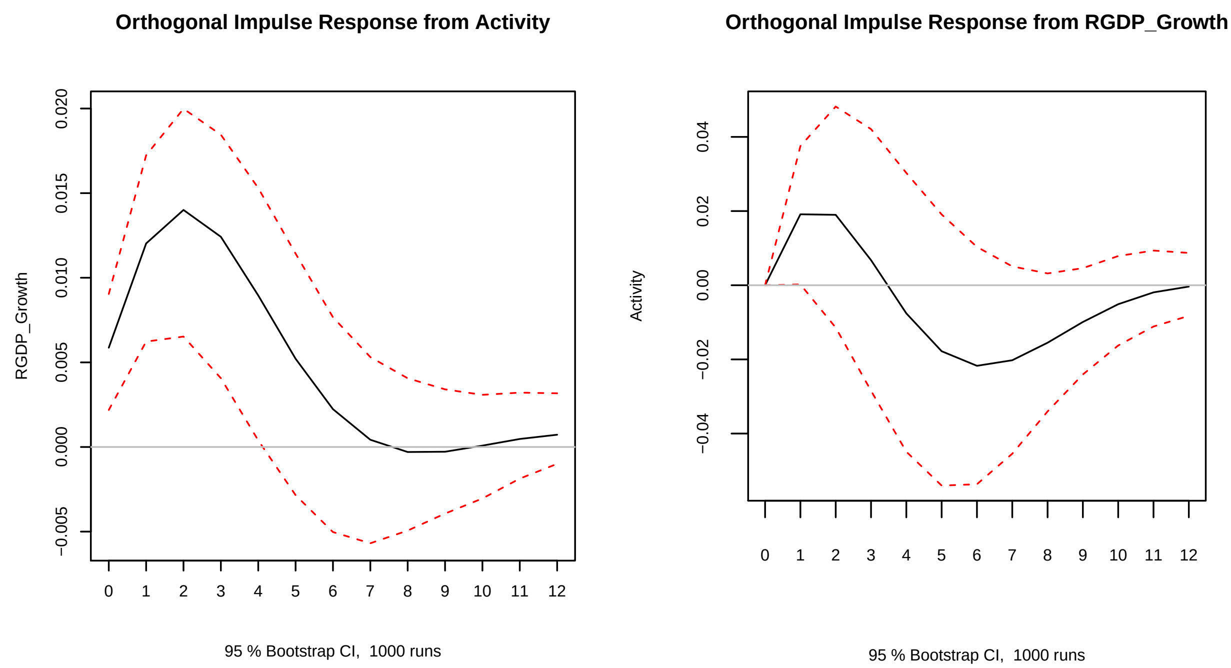

Figure 10: IRFs of Activity and real GDP growth in the Manufacturing sector

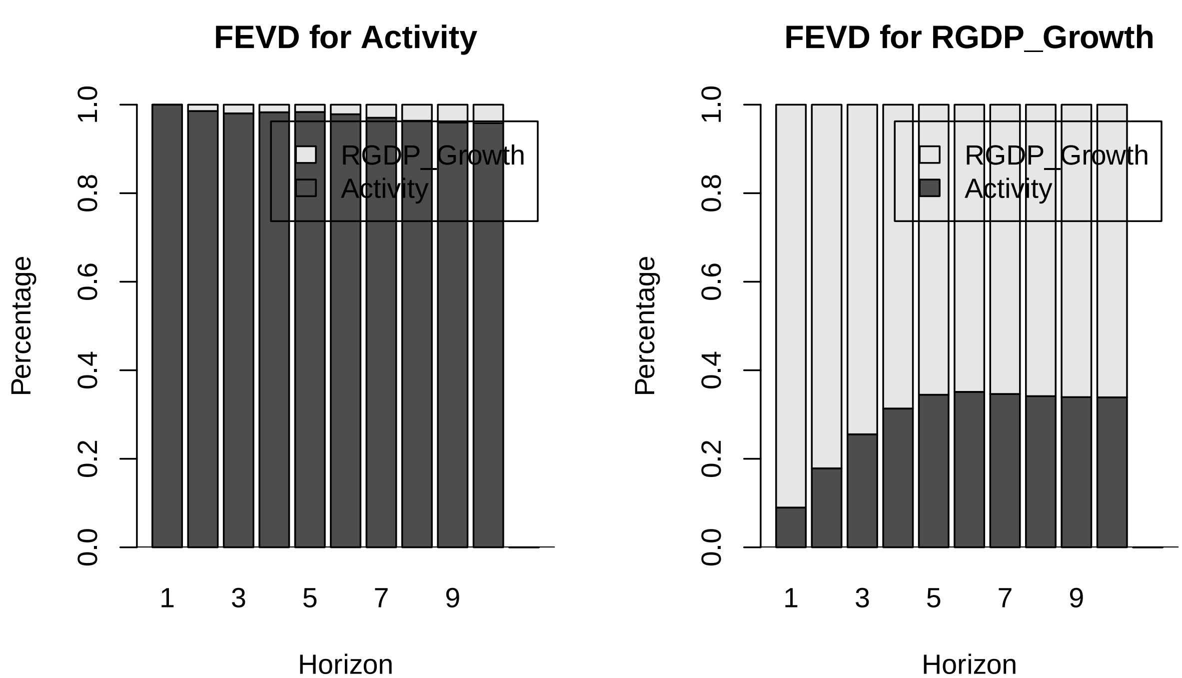

Figure 11: FEVDs of Activity and real GDP growth in the Manufacturing sector

the indicators based on current conditions. The indicators provided advanced warning of turning points, although there were a few false signals, especially over the ambiguous period of 2000-2003. The analysis could be expanded by further analysing the cyclical properties of the indicators in terms of duration, amplitude and steepness. Co-movement between cycles in the indicators and the business cycle could be analysed using the concordance index (Boshoff, 2005).

The results suggest that all three survey-based confidence indicators contain relevant information for the prediction of output growth. The lagged values of all three survey-based confidence indicators significantly Granger-caused real GDP growth, with limited evidence of Granger-causality in the reverse direction. The indicators had a positive and significant impact on real GDP growth in the VAR models. Shocks to the indicators accounted for a sizeable fraction of variation in economic activity. This 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 result, these confidence indicators are potentially useful for monitoring economic developments in a timely manner and for forecasting future economic activity. The new composite indicators seem to outperform the existing confidence indicators, in terms of tracking record, the stability of turning points, and the size of impulse responses.

A future avenue for investigation would be to assess the usefulness of the indicators in improving forecasts even after controlling for fundamentals, possibly using a large VAR system. The usefulness of the indicators for real-time forecasting could also be analysed, given that they are available around two months before many official series. An extension would be to test whether the relationship is non-linear or 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. Significant in-sample evidence of forecasting power does not guarantee significant out-of-sample ability. An alternative way to test the forecasting ability of the confidence indicators would be through an out-of-sample forecasting exercise at different horizons.

7 Results: Uncertainty

This section uses the quarterly BER business tendency surveys and the methodology described above to calculate composite sectoral and aggregate indicators of macroeconomic uncertainty for South Africa. Simple linear interpolation is used for the missing quarters throughout and all the indicators are scaled for graphical presentation. The indicators for uncertainty compared to other proxies for uncertainty and then related to economic activity in South Africa. A combined indicator is then constructed, which turns out to perform better than the individual indicators.

7.1 Uncertainty Indicators

Figure 12 illustrates the weighted sectoral Dispersion, Idiosyncratic and Aggregate uncertainty indicators. Indicators of uncertainty are quite volatile by construction (Girardi and Ruiter, 2015). In many cases the individual indicators for a sector are not significantly correlated, as discussed in Table 10 below. As a result, they do not always seem to point to the same periods of heightened uncertainty. For instance, the Dispersion and Aggregate uncertainty indicators for the Manufacturing sector show heightened uncertainty in 1998, during the recession, whereas the Idiosyncratic uncertainty indicator does not. In the Construction sector the Dispersion and Aggregate indicators point to heightened uncertainty in 2009 during the recession, whereas the Idiosyncratic uncertainty indicator does not.

The disaggrement is due to different calculation methods used to construct the proxies. The Dispersion indicator measures the disagreement in expectations, expressed as a share of the natural dispersion. The Aggregate and Idiosyncratic indicators measure respectively the average and standard deviation of realised expectation errors. Aggregate uncertainty will increase if more firms make similar and larger errors, while Idiosyncratic uncertainty will decrease if more firms make similar expectation errors.

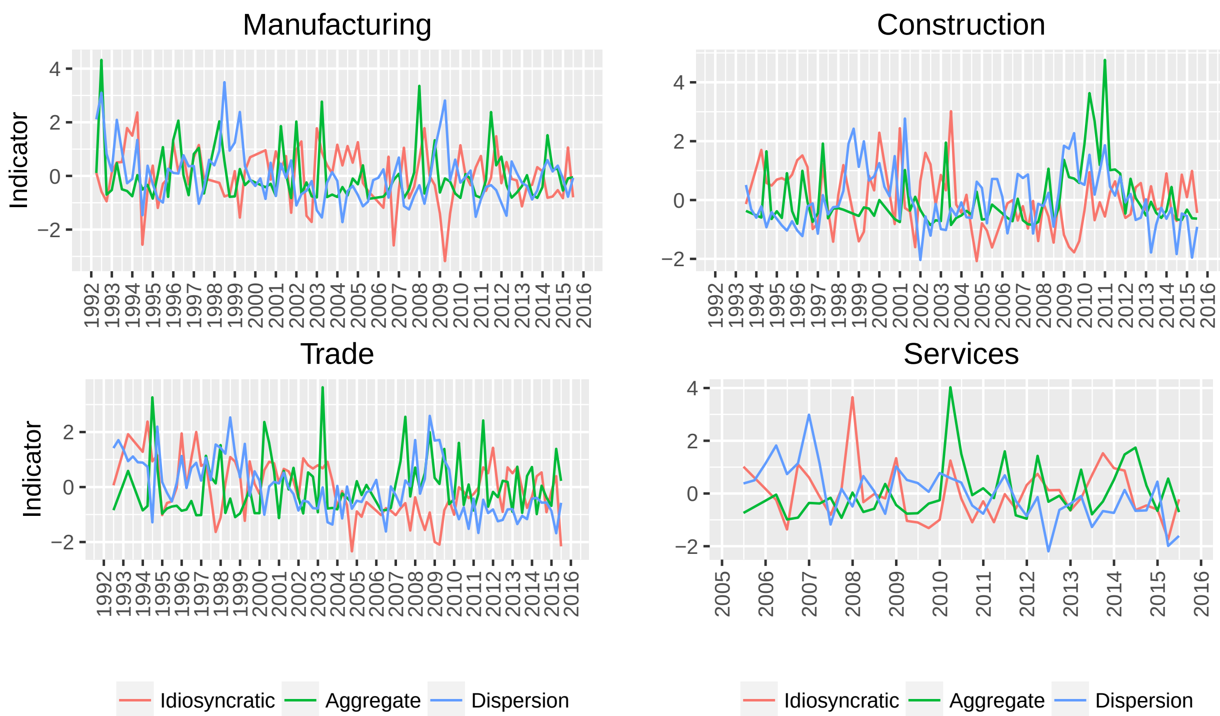

Figure 12: Weighted Sectoral Uncertainty Indicators

Figure 13 illustrates the three aggregated weighted uncertainty indicators, with recessionary periods shaded. As with the sectoral proxies, the indicators are relatively volatile and are not significantly correlated with each other, as reported in Table 9 below. Consequently, the indicators do not generally point to the same periods of heightened uncertainty. The Dispersion indicator seems to follow the strongest anti-cyclical pattern, with spikes during the recessionary periods. The Idiosyncratic indicator tends 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 firms 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. The Aggregate indicator seems to point to relatively fewer spikes in uncertainty, when firms were making similar and larger errors in their forecasts. The result for the unweighted indicators are similar to the weighted versions, as was the case for the confidence indicators.

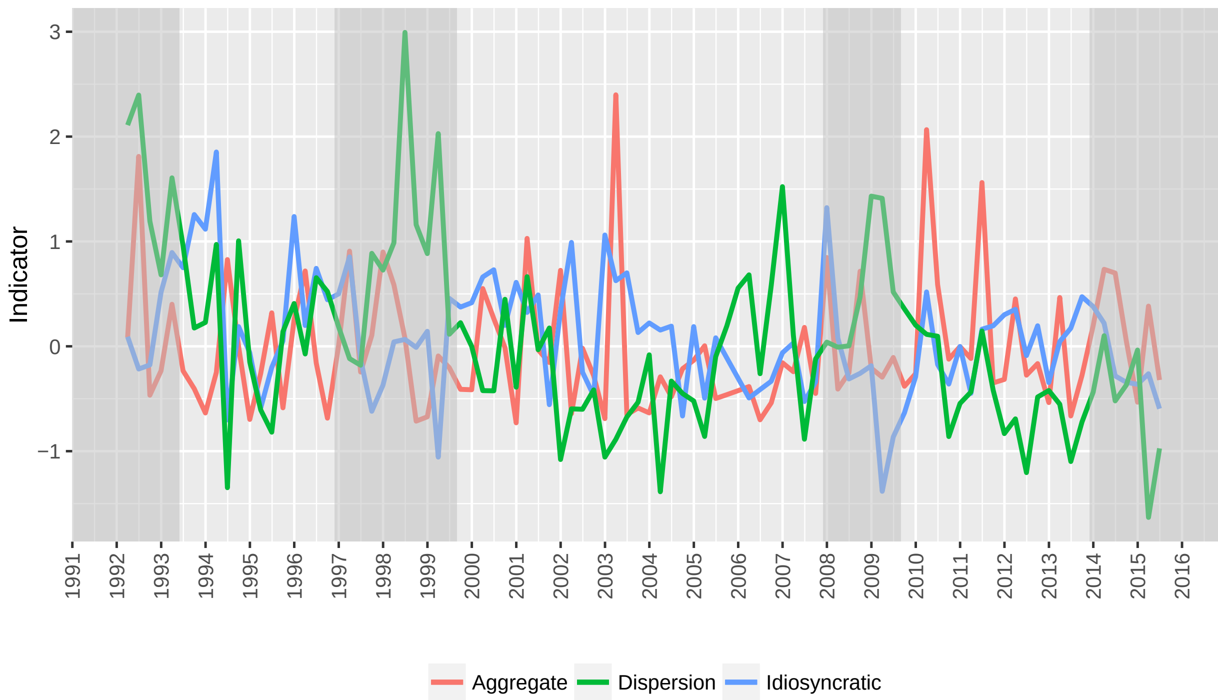

Figure 13: Weighted Uncertainty Indicators

The following section tests for this more formally be comparing the uncertainty indicators to alternative measures of uncertainty, as well as real GDP growth. A combined indicator is then constructed from all 5 proxies, which turns out to perform better than the individual indicators. The relationships are analysed for the aggregate variables, as well as for each sector separately. The advantage of also looking at specific sectors 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 offers a better chance of detecting the wait-and-see effect (Bachmann, Elstner and Sims, 2010).

7.2 Comparison and Evaluation

This section investigates two alternative indicators of uncertainty in South Africa. The first is the news-based Economic Policy Uncertainty index (EPU), constructed by Hlatshwayo and Saxegaard (2016). The second is a combination of implied and realised stock market volatility. The South African Volatility Index (SAVI) is a forecast of equity market risk on the Johannesburg Stock Exchange (JSE). It is modelled on the VIX, a popular measure for the volatility of the S&P 500, which has been used in a number of studies (e.g. Bloom (2009)). The SAVI is a forward-looking index that provides a daily prediction of market volatility in 3 months' time. It is calculated using implied volatilities obtained daily from specific Top 40 options (JSE, 2014). The SAVI is only available from June 2007. Following the literature (e.g. Bloom (2009), Valencia (2013), Bachmann, Elstner and Sims (2013) and Redl (2015)), an index of realised stock return volatility is calculated for the period before June 2007 and chained to the SAVI. The realised volatilities are calculated as the standard deviation of the daily JSE All Share index over each quarter.

The 3 survey-based uncertainty indicators can be combined with these two alternative indicators to form an overall Uncertainty indicator for South Africa. This is similar to the literature where uncertainty indicators are constructed from a range of different proxies, e.g. Baker, Bloom and Davis (2015), Redl (2015) and NWU (2016). This section then uses correlations, Granger causality tests, and bivariate VARs to provide some preliminary evidence on the dynamic effects of uncertainty shocks on the economy. The results presented below indicate that the combined measure is a better indicator, in terms of being correlated to movements in real output growth, than any of the separate components.

7.2.1 Correlations

Figure 14 illustrates the two alternative indicators, as well as the combined overall Uncertainty indicator, which is calculated as the average of all 5 indicators. The overall combined indicator seems particularly plausible as a proxy for macroeconomic uncertainty, as a number of large spikes coincide with periods when uncertainty in South Africa was thought to be relatively high. For instance, Uncertainty was relatively high during South Africa's Democratic transition up to 1994. There was quite a large spike, mainly in policy uncertainty, during the adoption of the new constitution in 1996. Other large spikes coincide with the East Asian and Russian crises and the concomitant recessionary period in 1998, the semi-recessionary period in 2003, the global financial crisis in 2008, and the start of the current recessionary period in 2014.

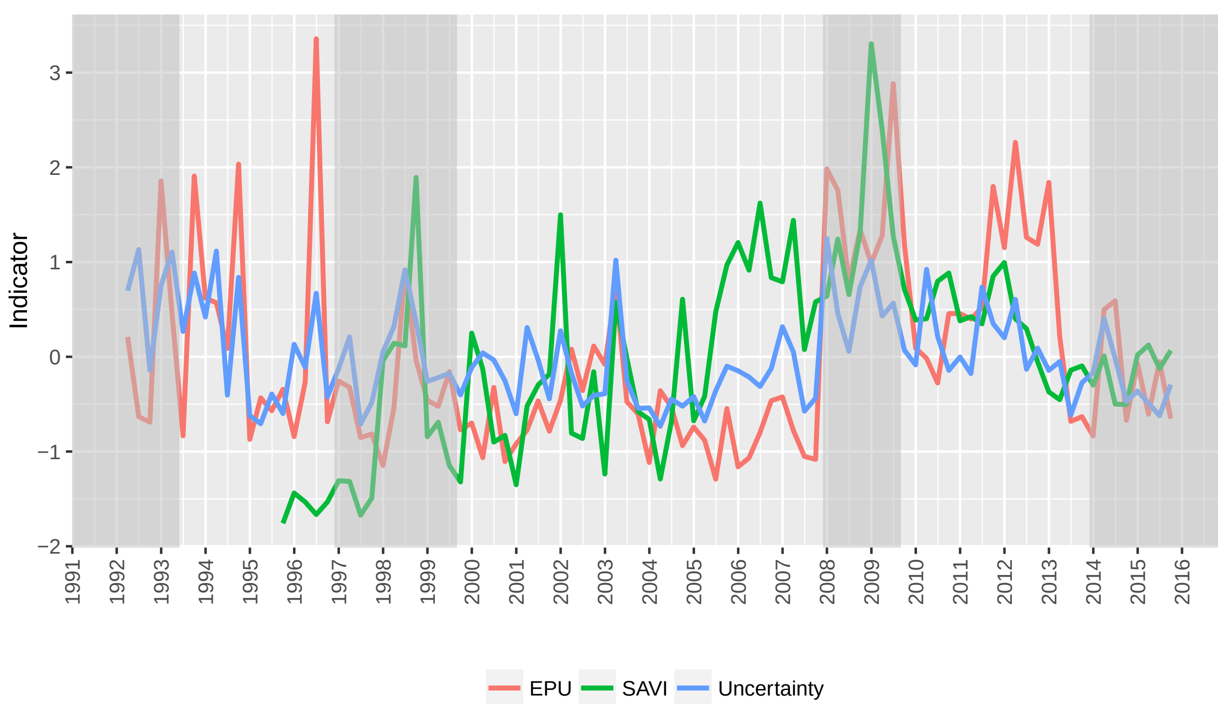

Figure 14: Weighted Uncertainty Indicators

Table 9 reports the contemporaneous correlations of the indicators and real GDP growth. The

Dispersion, EPU and overall Uncertainty indicators exhibit significant negative correlations with real GDP growth. These indicators are contemporaneously counter-cyclical, as is the case for the majority of the uncertainty indicators in the international literature (e.g. Bloom, 2014). The individual indicators are not significantly correlated with each other. This is not too surprising as they capture different types of uncertainty (Leduc and Liu, 2015). Survey-based measures capture the opinions of key agents in the economy and are driven by changes in firm-level uncertainty. Due to their qualitative nature, however, they are poorly equipped to fully capture large increases in uncertainty during extreme events (Bachmann, Elstner and Sims, 2013). The SAVI captures broad uncertainty in financial markets, but is derived from a specific segment of firms that are publicly traded, while the EPU is specifically focused on policy uncertainty. This motivates the use of a combined overall indicator, which captures different types of uncertainty from more than one source.

Table 9: Correlations in Levels

	Dispersion	Idiosyncratic	Aggregate	EPU	SAVI	Uncertainty
Dispersion						
Idiosyncratic	-0.03					
Aggregate	0.05	0.08				
EPU	0.09	0.11	0.07			
SAVI	0.17	-0.39***	0.03	0.27**		
Uncertainty	0.53***	0.38***	0.49***	0.62***	0.49***	
RGDP_Growth	-0.42***	0.09	-0.09	-0.28***	-0.09	-0.34***

Figure 15 illustrates the cross-correlograms for the uncertainty indicators and real GDP growth. All the indicators exhibit a significant negative correlation with real GDP growth, albeit at different horizons. All the indicators seem to lead changes in real GDP growth, except the Idiosyncratic indicator, which lags real GDP growth.

The story is broadly similar at sectoral level. Table 10 reports the contemporaneous correlations for the sectoral indicators and sectoral real GDP growth. The overall Uncertainty indicator for each sector is the average of the 3 survey-based measures. Only in some cases are the different uncertainty indicators significantly negative correlated with contemporaneous real sectoral GDP growth.

Table 10: Correlations in Levels

			Manufacturing				Construction	
Idiosyncratic	Idiosyncratic	Aggregate	Dispersion	Uncertainty	Idiosyncratic	Aggregate	Dispersion	Uncertainty
Aggregate	0.03				-0.06			
Dispersion	-0.31***	0.20*			-0.33***	0.35***		
Uncertainty	0.43***	0.73***	0.53***		0.36***	0.76***	0.60***	
RGDP	0.16	-0.01	-0.40***	-0.15	-0.27**	-0.11	-0.14	-0.31***

			Trade				Services	
Idiosyncratic	Idiosyncratic	Aggregate	Dispersion	Uncertainty	Idiosyncratic	Aggregate	Dispersion	Uncertainty
Aggregate	0.01				0.17			
Dispersion	0.08	0.00			0.10	-0.03		
Uncertainty	0.61***	0.57***	0.61***		0.68***	0.61***	0.57***	
RGDP	-0.07	-0.05	-0.36***	-0.27***	0.28*	-0.39**	0.41***	0.16

Figure 16 illustrates the cross-correlograms for the Manufacturing indicators and real GDP growth in the Manufacturing sector. The correlograms are similar to the aggregated results reported above, where the Dispersion and Aggregate measures have significant negative relationship with real GDP growth. The results for the other three sectors are similar, except for the Services sector, where only Aggregate uncertainty has a significant negative relationship with real GDP growth.

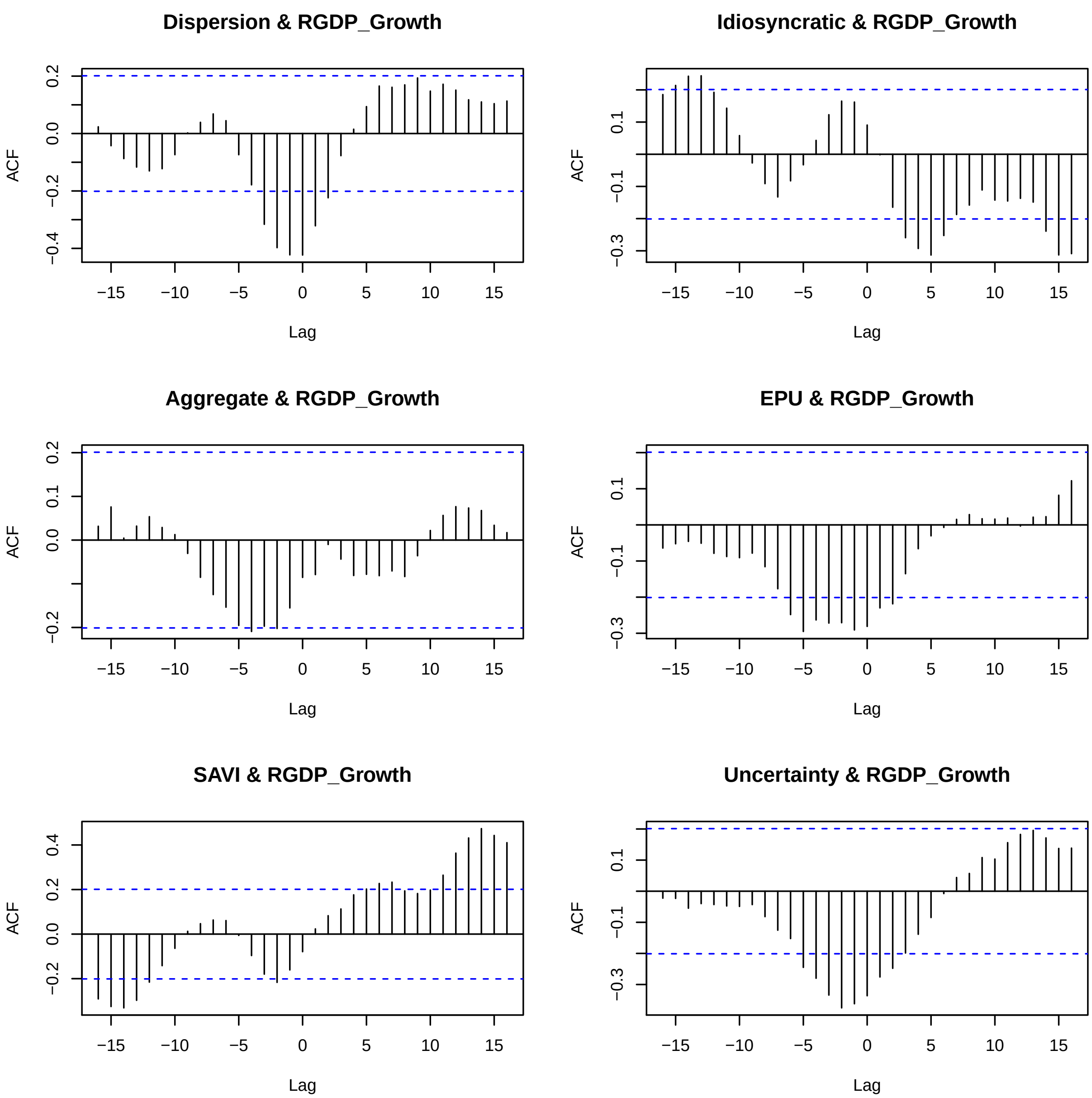

Figure 15: Cross-correlograms of uncertainty indicators and real GDP growth

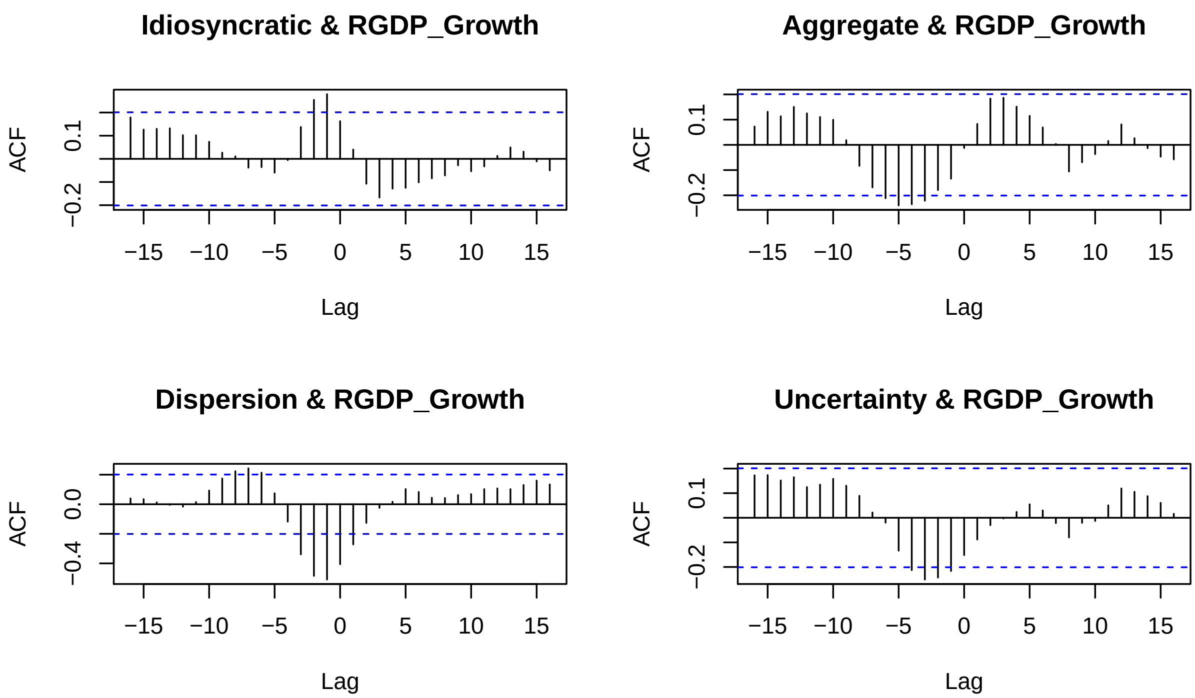

Figure 16: Cross-correlograms of Manufacturing uncertainty indicators and real GDP growth

7.2.2 Granger causality tests

Table 11 reports the results of Granger causality tests with the uncertainty indicators and real GDP growth. The results suggest little evidence of Granger-causality for the indicators and real GDP growth in either direction. The exceptions are real GDP growth Granger-causing Idiosyncratic uncertainty and Aggregate uncertainty Granger-causing real GDP growth.

Table 11: Granger causality tests

Granger causality H0:	statistic	p-value
Dispersion do not Granger-cause RGDP_Growth	0.678	0.51
RGDP_Growth do not Granger-cause Dispersion	0.124	0.88
Idiosyncratic do not Granger-cause RGDP_Growth	0.593	0.55
RGDP_Growth do not Granger-cause Idiosyncratic	5.088***	0.01
Aggregate do not Granger-cause RGDP_Growth	3.25**	0.04
RGDP_Growth do not Granger-cause Aggregate	0.205	0.81
EPU do not Granger-cause RGDP_Growth	1.156	0.33
RGDP_Growth do not Granger-cause EPU	1.771	0.15
SAVI do not Granger-cause RGDP_Growth	1.212	0.30
RGDP_Growth do not Granger-cause SAVI	1.121	0.33
Uncertainty do not Granger-cause RGDP_Growth	1.919	0.15
RGDP_Growth do not Granger-cause Uncertainty	1.013	0.36

The results for the sectoral indices are reported in Table 12. The results are not consistent across the sectors. There is limited evidence of Granger-causality in both directions for a few of the indicators in the Manufacturing and Construction sectors. There is no evidence of Granger causality in the Trade sector and the Services sector Aggregate indicator seems to lag real GDP growth in that sector.

Table 12: Granger causality tests

Granger causality H0:	Manufacturing	Construction	Trade	Services
Idiosyncratic do not Granger-cause RGDP_Growth	2.423*	0.799	1.383	1.054
RGDP_Growth do not Granger-cause Idiosyncratic	2.34*	4.752**	0.225	0.922
Aggregate do not Granger-cause RGDP_Growth	1.245	3.589*	0.854	0.298
RGDP_Growth do not Granger-cause Aggregate	2.068	0.062	0.181	3.852**
Dispersion do not Granger-cause RGDP_Growth	6.855***	0.232	0.11	0.048
RGDP_Growth do not Granger-cause Dispersion	0.743	0.063	0.629	0.54
Uncertainty do not Granger-cause RGDP_Growth	1.613	4.054**	1.493	0.322
RGDP_Growth do not Granger-cause Uncertainty	0.018	1.507	0.059	0.392

7.2.3 VAR Analysis

This section provides some preliminary evidence on the dynamic effects of confidence shocks on real economic activity. The VARs take the same form as those used to analyse confidence above. The uncertainty indicators enter in levels, while GDP enters as annual quarter-on-quarter growth rates. Unit root test indicate that all of the aggregate and sectoral uncertainty indicators are stationary. The appropriate number of lags are selected with the AIC, SC and HQ. The most parsimonious model is selected, provided that the diagnostic tests 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.

The uncertainty indicators are ordered first in a recursive identification strategy, with the Cholesky decomposition used to identify structural shocks. With this ordering, shocks to uncertainty are allowed to have a contemporaneous impact on output, but shocks to output have no contemporaneous impact on uncertainty. This is the identification strategy and ordering used in the literature (e.g. Bachmann, Elstner and Sims (2013), Girardi and Ruiter (2015), Baker, Bloom and Davis (2015), and Redl (2015)). Again, it can be motivated by the completion of the surveys before the release of most macroeconomic data (Leduc and Liu, 2015).

Figure 17 illustrates the IRFs of a bivariate VAR with Dispersion and real GDP growth. The left panel plots the responses of real GDP growth to an orthogonal shock in Dispersion, with 95% bootstrap confidence intervals. A shock to Dispersion is followed by a mildly significant decrease in real GDP growth. The right panel plots the responses of Dispersion to an orthogonal shock in real GDP growth. Following a shock to real GDP growth, there is no significant response in Dispersion. The results are similar for alternative orderings. The IRFs for the Aggregate, EPU, and SAVI indicators of uncertainty are almost identical. A shock to these indicators is associated with a mildly significant decrease in real GDP growth, while a shock to real GDP growth does not lead to a significant change in each of the uncertainty indicators.

Figure 18 illustrates the IRFs of a bivariate VAR with the overall Uncertainty indicators and real GDP growth. A shock to Uncertainty is followed by a significant decrease in real GDP growth by around 0.7% on impact, with a peak at 3 quarters. The impact on the growth rate is transitory, dying out after approximately 6 quarters. This result confirms the findings in most of the literature (e.g. Bachmann, Elstner and Sims (2013) and Redl (2015)), where innovations to uncertainty have protracted negative effects on economic activity.

Figure 19 illustrates the FEVDs for the overall Uncertainty indicator and real GDP growth. Up to around 20% of the movements in real GDP growth are explained by the Uncertainty indicator over

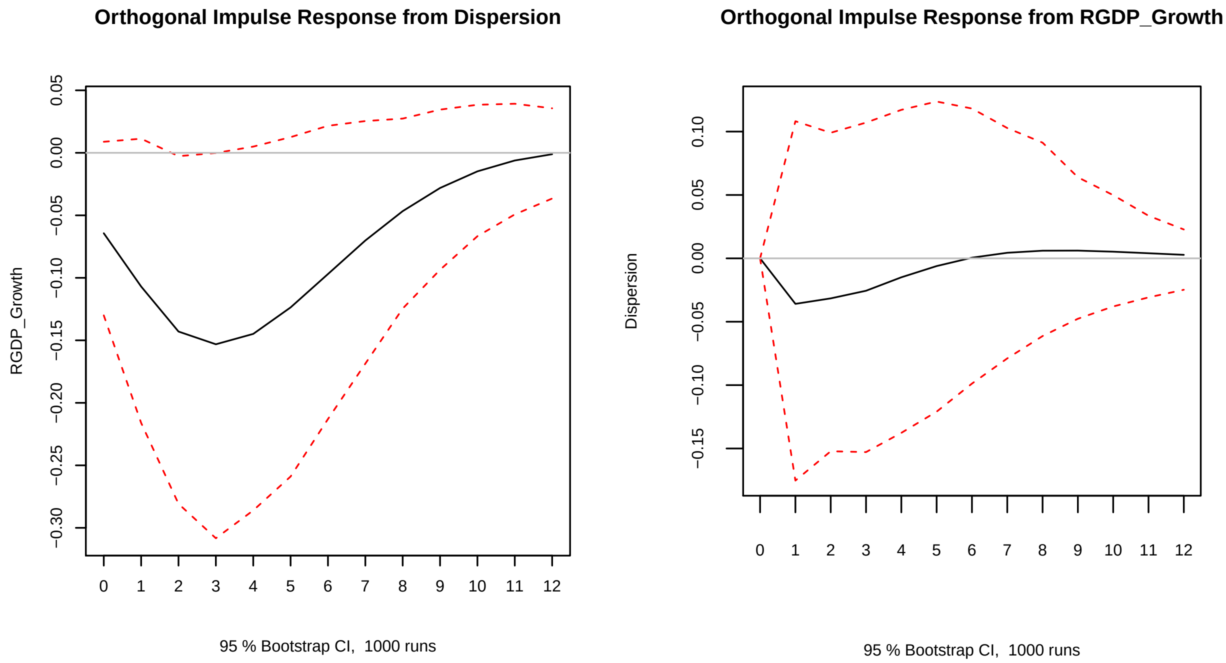

Figure 17: IRFs of Uncertainty and real GDP growth

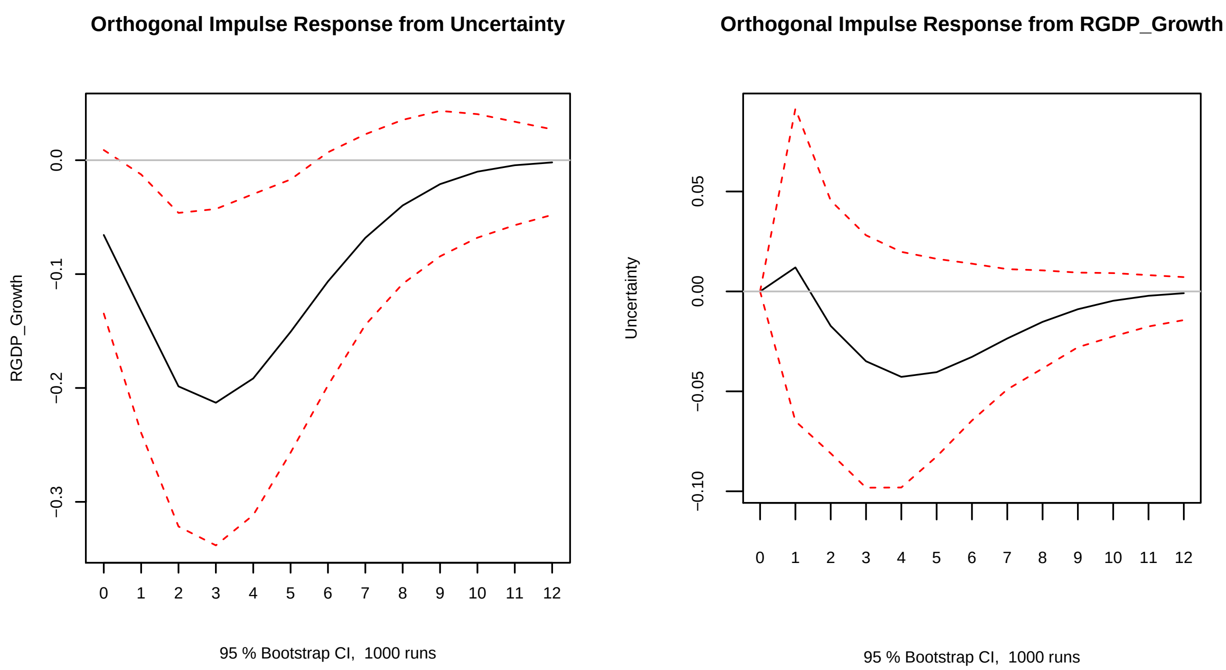

Figure 18: IRFs of Uncertainty and real GDP growth

the longer term, while real GDP explains about 2% of the variance in Uncertainty. This is in line with findings in the literature (e.g. Bachmann, Elstner and Sims (2013)).

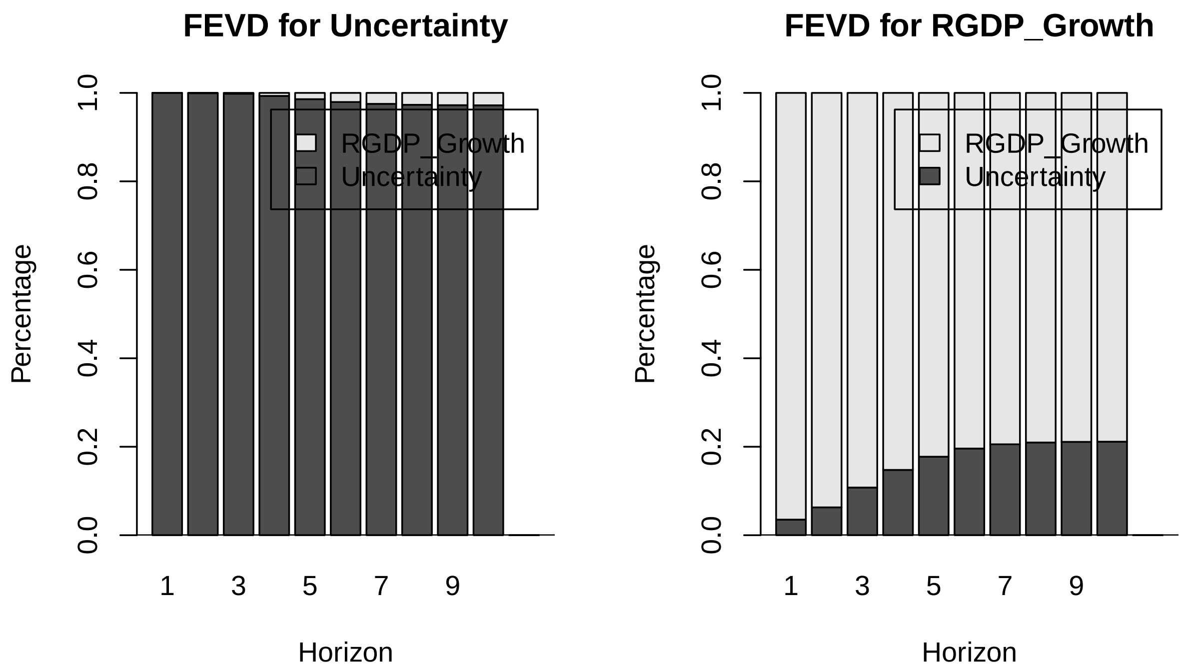

Figure 19: FEVDs of Activity and real GDP growth

The IRFs for the sectoral indicators are similar to these results. Figure 20 illustrates the IRFs of a bivariate VARs for the Manufacturing Uncertainty indicator and real GDP growth in the Manufacturing sector. A shock to Uncertainty is followed by a mildly significant decrease in real GDP growth, with a peak at 2 quarters. The FEVDs illustrated Figuer 21 show that around 10% of the movements in real Manufacturing GDP growth are explained by the Uncertainty indicator over the longer term.

7.2.4 Expanded VAR

Though instructive, the results from a bivariate system are prone to misspecification (Girardi and Ruiter, 2015). In order to test the robustness of the negative effect of uncertainty shocks, a number of authors have extended the baseline setup to include measures of confidence (Girardi and Ruiter (2015), Leduc and Liu (2015), Baker, Bloom and Davis (2015) and Bachmann, Elstner and Sims (2010)). Periods of increased uncertainty also tend to be periods of bad economic news. Confidence is usually included to control for the possibility that the impact of uncertainty may reflect respondents' perceptions of bad news rather than an uncertain future (Baker, Bloom and Davis, 2015).

Figure 22 and Figure 23 illustrate results from three-variable VARs including Confidence, Uncertainty and real GDP growth. Following Girardi and Ruiter (2015), Confidence is ordered first under a recursive identification scheme. 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

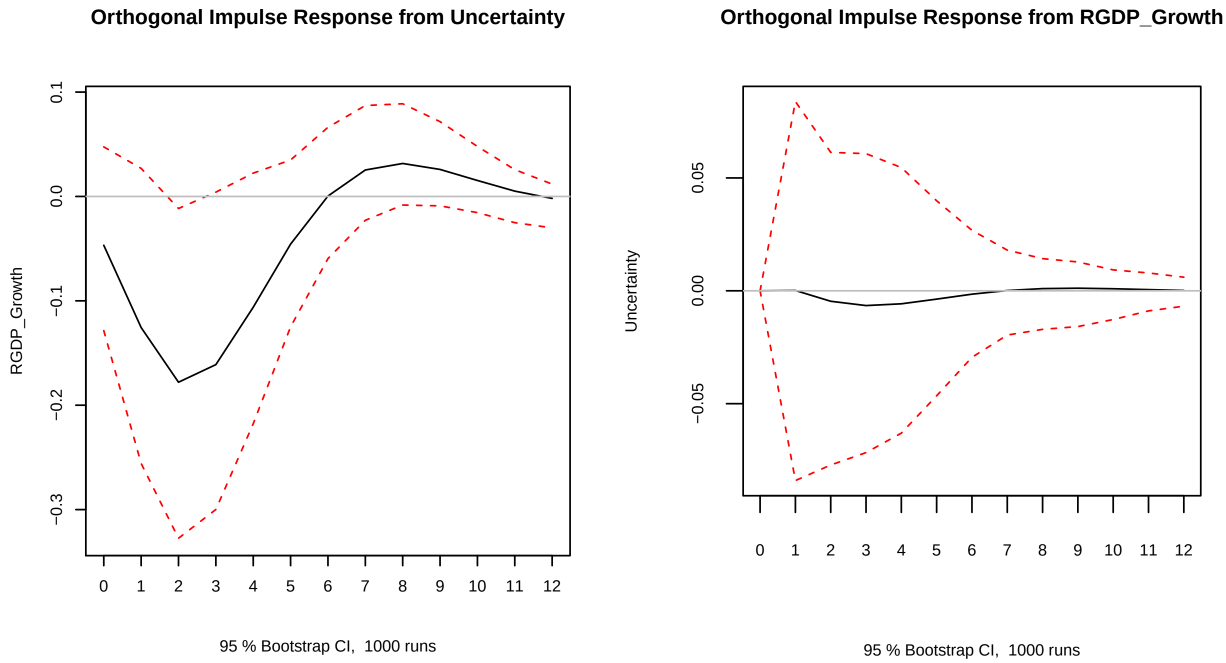

Figure 20: IRFs of Uncertainty and real GDP growth in the Manufacturing sector

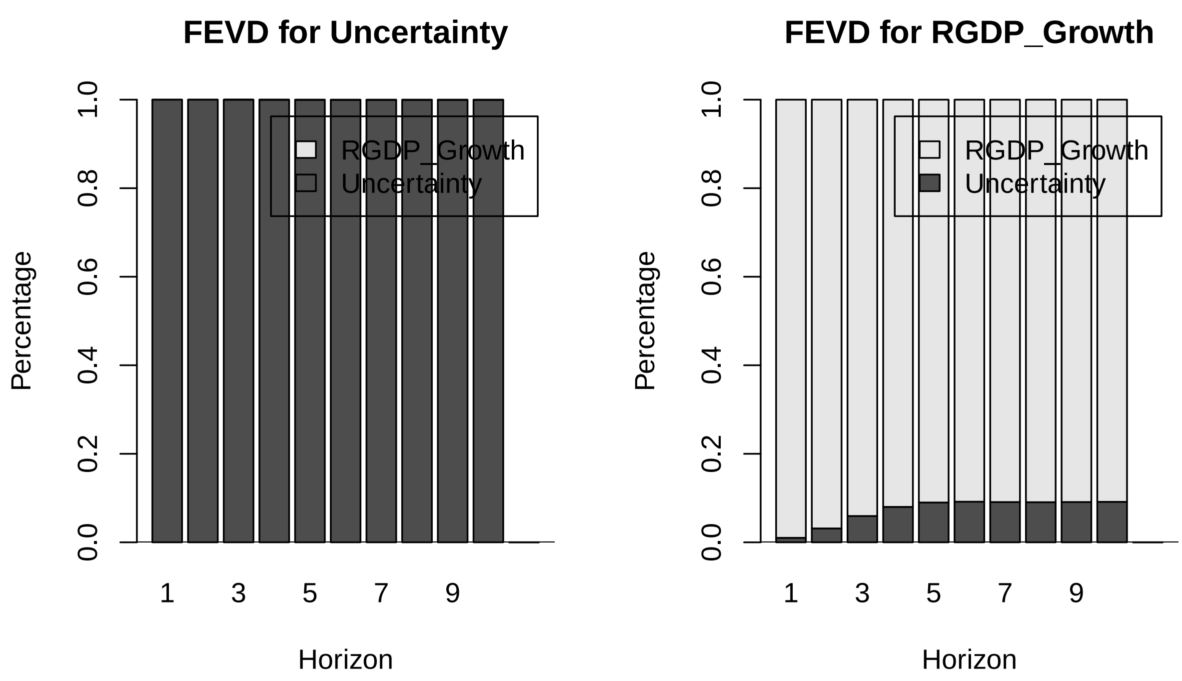

Figure 21: FEVDs of Uncertainty and real GDP growth in the Manufacturing sector

growth, while a shock to Uncertainty is followed by a decrease in real GDP growth. In contrast, a shock to real GDP growth is not followed by a significant increase in Confidence or Uncertainty.

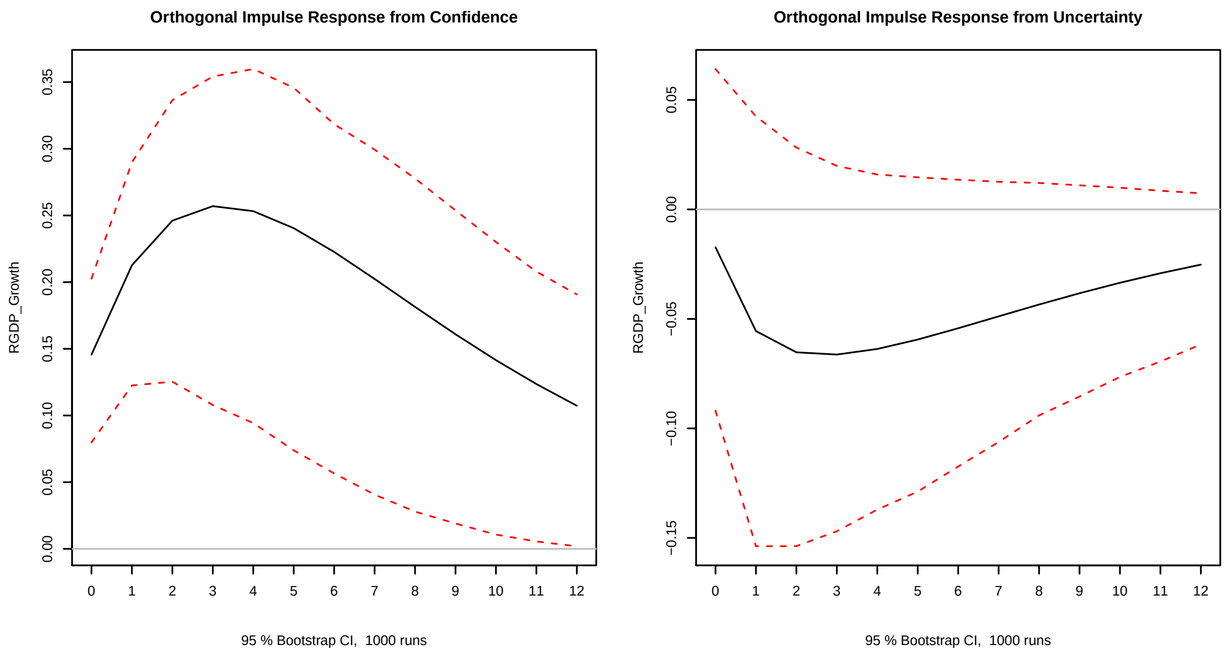

Figure 22: IRFs of real GDP growth to confidence and uncertainty

Compared to the previous results, the increase in output growth following a confidence shock is larger, while the decrease in output growth following an Uncertainty shock is smaller in magnitude and not quite significant. This suggests that confidence does proxy for part of the predictive power of the uncertainty measure (Baker, Bloom and Davis, 2015). Figure 24 illustrates the FEVDs for this 3-variable VAR. Up to more than half of the movements in real GDP growth are explained by Confidence over the longer term, while Uncertainty only explains around 3% of the movements in real GDP growth.

In future the results could be further testsed for robustness by estimating a larger extended VAR system. A number of authors have investigated the impact of uncertainty in larger VAR systems (e.g. Bloom (2009), Bachmann, Elstner and Sims (2013), and 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 VARs are then typically estimated in (log) levels, as opposed to the growth rates used above, which may allow longer term relationships to emerge.

7.2.5 Summary and Suggeted Further Analysis

This section has presented 3 survey-based indicators of uncertainty, as well as two additional popular proxies from the literature: stock market volatility and the news-based EPU created by Hlatshwayo and Saxegaard (2016). All the indicators appear to be counter-cyclical in the sense that they exhibit a significant negative correlation with real GDP growth, albeit at different horizons. Most of the indicators seem to lead changes in real GDP growth.

None of the uncertainty proxies are a perfect measure of a multidimensional and complex phenomenon,

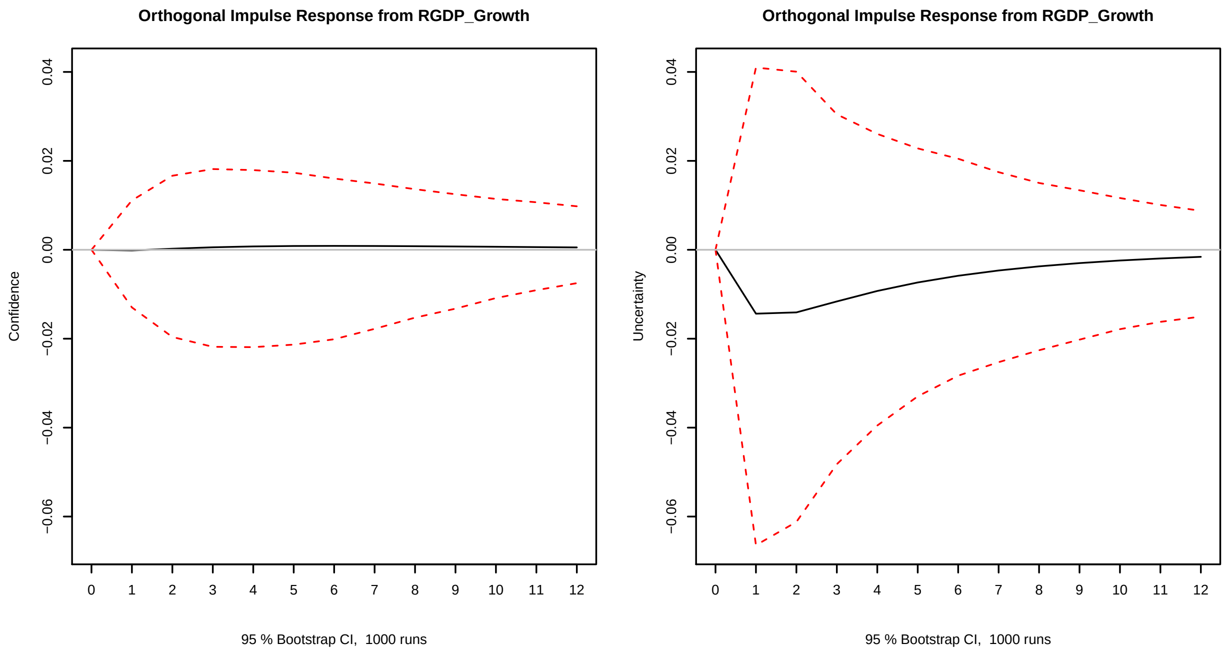

Figure 23: IRFs of confidence and uncertainty to real GDP growth

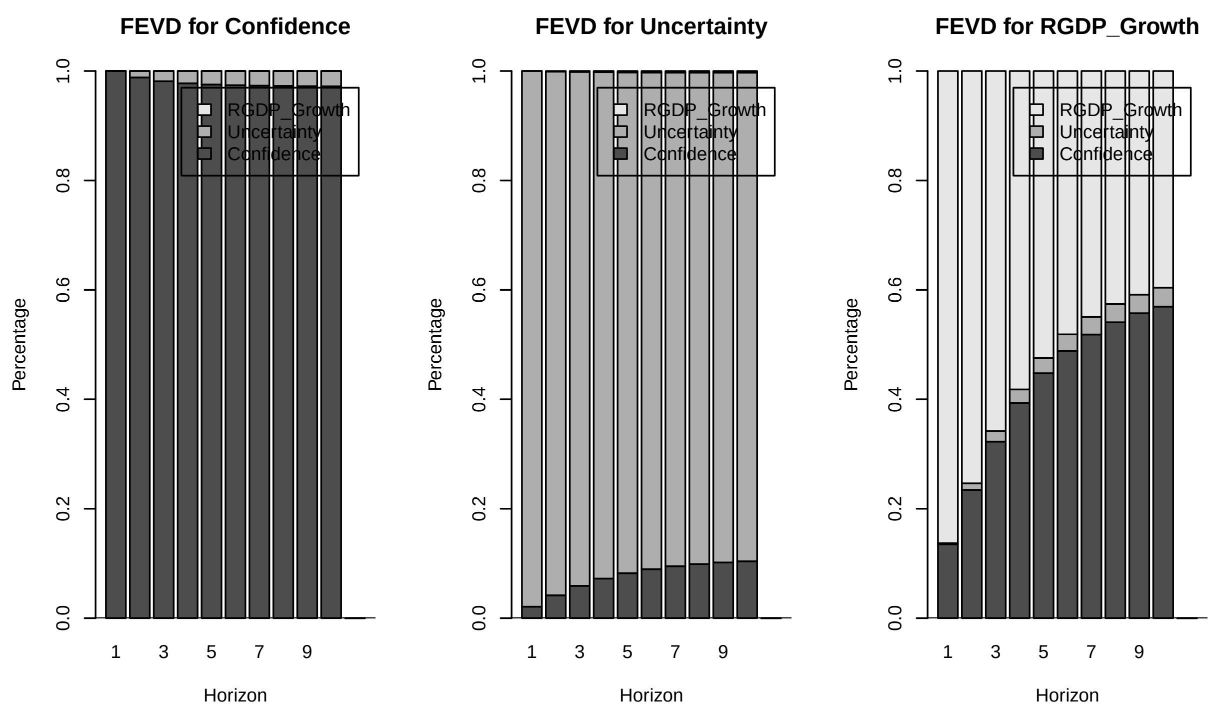

Figure 24: FEVDs of Uncertainty and real GDP growth in the Manufacturing sector

but all of them can potentially contribute to the understanding of the effects of uncertainty on economic activity (Bachmann, Elstner and Sims, 2013). The 5 indicators were therefore combined to form an overall Uncertainty indicator, reflecting different sources of uncertainty from the different proxies. This combined indicator appeared to be a plausible indicator of macroeconomic uncertainty in South Africa, reflecting key economic events. It also appeared to perform more successfully in tracking real GDP growth rates than any of the individual components separately.

The results from the VAR analysis indicated that a shock to this Uncertainty indicator was followed by a significant decrease in real GDP growth, with a peak at 3 quarters. The impact on the growth rate was transitory, dying out after approximately 6 quarters. This result confirms the findings in most of the literature, where innovations to uncertainty have protracted negative effects on economic activity. The results from an expanded 3 variable VAR, which included a measure of confidence, confirmed the negative relationship, although the Uncertainty shock lost its statistical significance.

A future avenue for investigation would be to test 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. An extension would be to test whether the relationship is non-linear and asymmetric, depending on 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.

8 Conclusion

This paper has attempted to make two contributions to the literature on business sentiment in South Africa. The first was to construct new composite indicators of confidence and uncertainty for South Africa, based on the microdata from the BER's business tendency surveys. The second was to examine the comovement between the sentiment indicators and economic activity. The aim was to examine whether these survey-based indicators have plausible and significant relationships with real economic activity.

The composite confidence indicators seemed plausible and exhibited a significant positive correlation with real GDP growth. The indicators provided advanced warning of turning points, although there were a few false signals. The results suggested that the survey-based confidence indicators contained relevant information for predicting output growth. A shock to the confidence indicators was followed by a significant increase in real GDP growth in the VAR models. This was the case for the aggregate indicators as well as the sectoral indicators. This implies that these confidence indicators are potentially useful for monitoring economic developments in a timely manner and for forecasting future economic activity. The new composite indicators also seem to outperform the existing confidence indicators.

Three composite survey-based indicators of uncertainty were calculated, as well as two additional popular proxies from the literature. All the indicators appeared to be counter-cyclical in the sense that they exhibit a significant negative correlation with real GDP growth, albeit at different horizons. Most of the indicators seem to lead changes in real GDP growth. The 5 indicators were combined to form an overall Uncertainty indicator, reflecting different sources of uncertainty from the different proxies. This combined indicator appeared to be a plausible indicator of macroeconomic uncertainty in South Africa, reflecting key economic events. It also appeared to perform more successfully in tracking real GDP growth rates than any of the individual components separately. The results indicated that a shock to the Uncertainty indicator was followed by a significant decrease in real GDP growth. The results from an expanded 3 variable VAR, which included a measure of confidence, confirmed the negative relationship, although the Uncertainty shock lost its statistical significance.

Hopefully these new composite indicators of confidence and uncertainty will be useful for a range of applications. For instance, the Confidence indicators might be useful for forecasting and nowcasting exercises and to provide and early warning signals for business cycle turning points. The Uncertainty indicator could be used to further investigate the importance of uncertainty shocks for business cycle fluctuations and credit cycles.

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