1 Methods for Aggregating Disparate Qualitative Survey Responses: An Application to Business Sentiment in South Africa

1.1 Introduction

The global financial crisis was associated with unusually low levels of confidence and heightened uncertainty among firms. According to the European Central Bank (2013), weak business sentiment contributed to a large extent to the Great Recession and to the lacklustre subsequent recovery. More recently, there has been increased uncertainty around the implications of the Brexit referendum (Jackson, Tetlow and Kahn, 2017) and the policy direction under President Trump (Shen, 2017). The International Monetary Fund (2017) cited elevated political uncertainty and weak consumer and business confidence when it marked down South Africa's growth forecast for 2018. The idea that weak business sentiment influenced economic activity has inspired a substantial literature examining the impact of changes in sentiment, and especially uncertainty, on investment and output decisions.

Business sentiment covers two distinct concepts: *confidence* and *uncertainty*. For the purposes of this chapter, business confidence is the degree of optimism that firms hold, or their perceptions of, current and future business conditions (Mendicino and Punzi, 2013). Business uncertainty is the inability of firms to forecast the probability of future events occurring (Knight, 1921). It is challenging to measure these concepts (Santero and Westerlund, 1996), as both are not directly observable and their definitions are difficult to operationalise.

The aim in this chapter is to explore aggregation methods for estimating business confidence and uncertainty in South Africa, using the microeconomic data from the Bureau for Economic Research (BER) business tendency surveys. Although measuring business sentiment is challenging, survey-based indicators can be helpful in discovering agents' opinions on future economic developments (Organisation for Economic Co-operation and Development, 2003).

To date, there has been little research on business sentiment in South Africa, in part due to the difficulty of measurement. As far as research on confidence is concerned, only two business confidence indicators are regularly published for South Africa: the South African Chamber of Commerce and Industry Business Confidence Index (SACCI BCI) and the BER Business Confidence Index (BER BCI). The SACCI BCI is a composite measure of economic activity, rather than a confidence indicator in the way used in the literature. The BER BCI is a measure of confidence derived from the BER's business tendency surveys. It is based on a single question on current conditions. The survey responses are weighted in an ad hoc manner, and the services sector survey is excluded from the calculation. As far as research on uncertainty, as opposed to confidence, is concerned, only a few studies have created proxies for uncertainty in South Africa (e.g. Redl (2015) and Hlatshwayo and Saxegaard (2016)). No study has fully exploited the information contained in the BER business tendency surveys to construct proxies for business uncertainty in South Africa.

The challenge in aggregating the microeconomic data from the BER business tendency surveys is to identify an underlying pattern from the disparate views of individual agents. In the chapter, an attempt is made to capture the full distribution of the qualitative survey responses, by calculating the first and second weighted cross-sectional moments of the distribution. The composite indicators of business confidence and uncertainty are based on these moments.

Two composite confidence indicators are calculated in this chapter: the cross-sectional mean of responses to questions on current business conditions, and the cross-sectional mean of responses to questions on expected future business conditions (Organisation for Economic Co-operation and Development, 2003). Three composite uncertainty indicators are calculated: the scaled cross-sectional standard deviation of forward-looking responses (Girardi and Reuter, 2017); the cross-sectional mean of individual firm forecast errors; and the cross-sectional standard deviation of forecast errors (Bachmann, Elstner and Sims, 2013; Arslan *et al.*, 2015).

The new composite indicators attempt to improve on the existing measures of sentiment for South Africa. The indictors incorporate the survey responses from questions on general business conditions, output, employment, orders placed and profitability. For each question, the responses are weighted by firm size and subsector size to produce sectoral indicators, including the services sector. The sectoral indicators are then weighted by GDP share to produce the overall aggregate composite indicators.

The validity of the indicators is assessed by comparing them with events that were thought to coincide with large changes in confidence and uncertainty, as well as with existing measures for South Africa. The two confidence indicators are compared with the BER BCI and the SACCI BCI. The three composite uncertainty indicators are compared with a measure of financial market uncertainty and the economic policy uncertainty indicator created by Hlatshwayo and Saxegaard (2016). A composite overall measure of uncertainty is constructed, which combines the survey-based uncertainty indicators with the measures of financial market and economic policy uncertainty. Similar to the previous chapter, the indicators are evaluated to determine whether they improve on the existing indicators. In this chapter, the indicators are evaluated according to their comovement with real GDP growth. The leading indicator properties of the confidence indices are also evaluated, in terms of the timing of their turning points and their concordance with the official SARB business cycle.

There has been little analysis of this relationship in the South African context (e.g. Pellissier (2002) and Redl (2015)). The newly constructed sentiment indicators are therefore exploited to further examine the relationship between business sentiment and real economic activity in South Africa. This demonstrates the usefulness of the aggregation methods and provides an additional validity test of the estimated indicators. In particular, the hypothesis is tested that there is significant comovement between the sentiment indicators and real GDP growth, using a standard VAR framework. The relationship between the indicators and real GDP growth is investigated, including the timing of the relationship and the extent to which correlation is conditional on other economic variables. The following sections provide a review of the literature on confidence and uncertainty.

1.2 Confidence

For the purposes of this chapter, business confidence involves firms' perceptions of, or degree of optimism regarding, current business conditions and the expected future business climate (Mendicino and Punzi, 2013). This section begins with a review of the theoretical links between confidence and macroeconomic outcomes. The section then discusses the measurement challenges and the evidence on the impact of confidence on economic outcomes.

1.2.1 Theory on Confidence and Economic Outcomes

While confidence measures are popular indicators with the media and business players, the stance of the academic literature on the value of these indicators is more ambiguous (Barsky and Sims, 2012). A review of the literature suggests three alternative views, which range from the view that confidence measures play an important causal role in the business cycle, to the view that they contain useful predictive information but play a limited causal role, to the view that they have no value, even in forecasting. In this section these three views are briefly discussed.

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

Thus, psychological factors are drivers of consumption and investment decisions in the face of uncertainty, due to the difficulty of making accurate forecasts (Pagan, 2013). For firms, waves of optimism and pessimism may cause errors in their expectations about future demand and profits. When firms are optimistic about future demand and profits, they decide to accumulate capital. If their expectations are not met, there will be a period of reduced investment, which may cause a recession (Beaudry and Portier, 2004). These errors therefore generate cycles through increases and decreases in investment (Leduc, 2010).

For consumers, optimistic income expectations lead them to increase their discretionary expenditures. These expectations depend not only on economic fundamentals, such as income or prices, but also on psychological factors. Psychological factors therefore influence consumers’ perceptions of their economic environment and may become an independent source of economic fluctuations through their impact on their decisions (Mendicino and Punzi, 2013). Blanchard (1993), for instance, argued that a negative consumption shock, which was associated with an exogenous shift in pessimism, was the cause of the 1990/1991 US recession. Akerlof and Shiller (2015) argued that deteriorating confidence, one of the main elements of animal spirits, was an important reason for the global financial crisis and subsequent recession.

Models with multiple equilibria provide a potential causal link between confidence and fluctuations in economic activity, where the equilibria may be determined by sentiment (Taylor and McNabb, 2007). The level of confidence is a potential variable that can determine which equilibrium occurs. For example, if a crisis of confidence causes a banking panic, the economy may settle at a suboptimal equilibrium, in respect of social welfare. If confidence is high, the economy may settle at an optimal equilibrium (Leduc, 2010). In this context, confidence is a prediction of a future outcome, which may become self-fulfilling (Akerlof and Shiller, 2015).

According to the animal spirits view, therefore, confidence has a potentially important causal impact on economic outcomes. In contrast, the so-called ‘news’ view argues that confidence indicators contain useful predictive information for economic output, but play a limited causal role.

According to the news view, any relationship between confidence measures and subsequent real activity means that confidence measures contain information about current and future fundamentals of the economy (Barsky and Sims, 2012). Confidence can proxy for news that agents receive about future productivity, which is not yet reflected in econometricians' information sets, by aggregating information from various sources (Cochrane, 1994; Barsky and Sims, 2012). Confidence indicators reflect agents' expectations about future fundamentals and economic conditions, which are not summarised in other macroeconomic variables. When agents are optimistic, they give positive responses to surveys. These are confirmed, on average, and real activity eventually increases as predicted by the confidence indicator (Carroll, Fuhrer and Wilcox, 1994).

From the rational expectations point of view, confidence should reflect the expected values of economic fundamentals and should not offer any additional predictive information (Beaudry and Portier, 2004). However, a number of studies (e.g. Beaudry and Portier (2004) and Van Aarle and Kappler (2012)) analyse models where agents receive imperfect signals about future productivity growth and use these signals to make investment decisions. In this context, confidence refers to a state where agents receive an above-average signal, which may generate a wave of optimism. Rational agents then learn gradually about the true state of the economy and adjust their expectations. In this environment, occasional recessions reflect the availability of good quality information on which agents act.

Other factors, such as frictions in capital markets, may explain the predictive information contained in confidence indicators. For instance, an increase in confidence may reflect higher future income, but borrowing constraints can prevent higher current consumption in anticipation of an increase in income. As a result, consumption will increase only when actual income increases, and a rise in consumer confidence will predict the future consumption increase (European Central Bank, 2013).

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

1.2.2 Empirical Findings

The empirical literature has tried to establish whether there is predictive information in confidence indicators, over and above economic fundamentals, and if so, whether confidence has a separate causal impact on economic activity. Although the findings have not been conclusive, the majority of studies seems to find that confidence indicators are at least positively related to real economic activity (Taylor and McNabb, 2007). The inconclusive findings may be due to two main challenges: how to construct proxies for confidence and how to establish whether it has a separate causal impact on real economic activity.

1.2.2.1 Measuring Confidence

As confidence cannot be observed or measured directly (Santero and Westerlund, 1996), analysts typically aggregate responses from business and consumer surveys. These surveys usually contain a small number of qualitative questions, which can be answered quickly by respondents. Indicators are derived from the subjective answers to questions on past, current and future developments. The assumption is that agents form opinions about economic conditions before a specific business activity is implemented (e.g. new production plans, employment, or purchases). These opinions may be called 'confidence'. The most important advantage of these surveys is that they are available long before official statistics become available. Moreover, they are not subject to revisions and avoid problems with trends and seasonality.

The most common and widely used method to aggregate survey responses is to calculate so-called balance statistics. 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 (Organisation for Economic Co-operation and Development, 2003).

Although balances are by far the most common method used by statistical agencies and analysts to aggregate the surveys, a few more sophisticated methods have been discussed in the literature, including a probabilistic approach, a regression approach, and a latent factor approach (Nardo, 2003).[1] However, these approaches usually require actual quantitative reference series for the relevant variables, which is restrictive in the case of business confidence, where quantitative reference series are unavailable. Moreover, these methods can become unreliable when exceptional events have a large impact on the correlation between the survey data and the quantitative reference series (United Nations, 2015).

Nevertheless, the evidence suggests that balance statistics tend to produce indicators that are very similar to those produced by more sophisticated methods. For instance, the Italian National Statistical Agency found a very high correlation between balances and more sophisticated indictors when using three-option responses (Organisation for Economic Co-operation and Development, 2003). Driver and Urga (2004) assessed different ways of aggregating qualitative data from the UK employers' business survey into quantitative indicators for a number of variables. They found that the balance statistic was a satisfactory aggregation method for the survey responses on output, investment, and exports. Weighted balance statistics are therefore used in this chapter to calculate summary statistics for the responses to each survey question.

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

Composite confidence indicators of this type are available for most countries. The European

[1] The probabilistic approach assumes a probability distribution for the variable concerned, and the measure is a function of this specific probability distribution. The regression approach uses the relationship between survey responses of the past and actual values to quantify respondents' expectations about the future. The measures are a function of specific regression models (Nardo, 2003). In the latent factor approach, the percentages of each response are a function of a common 'latent measure' observed by respondents, but not by econometricians.

Commission, for instance, builds composite indicators by aggregating the survey responses from five sectors, using multiple questions on current and expected conditions. For example, the industrial indicator is an average of the balances of questions relating to production expectations, stocks of goods (with an inverted sign), and order books, while the retail trade indicator is an average of balances of questions relating to the present and future business situation and stocks (with an inverted sign) (Organisation for Economic Co-operation and Development, 2003). The aggregate Economic Sentiment Index is a weighted average, using value added shares, of confidence in the manufacturing, construction, retail, and services sectors, as well as for consumers (European Central Bank, 2013). Taylor and McNabb (2007) and Mendicino and Punzi (2013) used these composite confidence indicators for a number of European countries in investigating the impact of confidence on economic activity.

Another prominent example is the German Ifo Business Climate Indicator, which is used as 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 (United Nations, 2015). The results for the manufacturing, construction, wholesale and retail sectors are weighted according to the importance of the industry.

Bachmann, Elstner and Sims (2013) used the Ifo Business Climate Survey, as well as the Philadelphia Fed's Business Outlook Survey, to calculate composite indices of current and expected conditions. Barsky and Sims (2012) used the Consumer Sentiment Index, published by the University of Michigan as a composite forward-looking measure of confidence. Kabundi (2004) used a dynamic factor model to calculate a composite indicator from the French Statistics Institute's business survey data.

Two indicators of confidence are published in South Africa: the BER BCI and the 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 (Q1) that appears in all of the surveys: "Are prevailing business conditions: satisfactory, or unsatisfactory?" The BCI is the weighted percentage of respondents who rated prevailing business conditions as 'satisfactory' and is therefore based on the perceptions of business people (Kershoff, 2002). The survey responses are weighted (except the building survey), and the BER BCI is calculated as the unweighted mean of five sectoral indices (excluding the services sector). The BER BCI is an index of current conditions, as opposed to expected conditions, 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 thought to have the greatest influence on the business mood. These include the exchange rate, inflation, the prime rate, retail sales volumes, credit extension, commodity prices, import and export volumes, new vehicle sales, utility services, manufacturing production, building plans passed, and the stock market index. The SACCI BCI is an *ex post* measure of actual activity, which is dependent on external macroeconomic variables. The rationale is that recent business activity is indicative of the degree of business confidence (SACCI, 2011). In this sense, the SACCI BCI is a composite measure of economic activity, rather than a confidence indicator in the way it is defined in the literature. This chapter aims to calculate improved composite indicators of business confidence based on the BER business tendency surveys.

1.2.2.2 The Impact of Confidence

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

The empirical literature has often investigated the extent to which confidence indicators contain predictive information over and above economic fundamentals (United Nations, 2015). A number of studies have shown that both consumer and business confidence indicators provided valuable information for forecasting real activity, which was not contained in other economic variables (e.g. Santero and Westerlund, 1996; Ludvigson, 2004; Kabundi, 2004; Parigi and Golinelli, 2004; Taylor and McNabb, 2007; Leduc and Sill, 2013; Mendicino and Punzi, 2013; Martinsen, Ravazzolo and Wulfsberg, 2014; and Kilic and Cankaya, 2016).

In an influential study, Barsky and Sims (2012) found that positive shocks to consumer confidence led to significant, slow-building, and permanent responses in consumption and income. If confidence contained no news about future fundamentals, and reflected only animal spirits, one would expect transitory responses. Barsky and Sims (2012) concluded that their results supported the 'news' view of confidence.

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

The forecasting ability of confidence indicators might be offset by other indicators during ordinary times, while increasing notably during unusual events (United Nations, 2015). The European Central Bank (2013) found that shocks to confidence played a relatively small role during normal times, but were important during more extreme episodes such as financial crises and recessions. The impact was asymmetric: large decreases in 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.

Even if confidence indicators are just a synthesis of economic variables and do not carry information over and above other economic series, they may still be useful for monitoring economic developments and for real-time forecasting of economic activity. This is because they are available before official quantitative statistics and are subject only to limited revisions (Santero and Westerlund, 1996). In the euro area, for instance, official statistics are released at least 45 days after the reference month (e.g. data for January is only available by mid-March). Business surveys are usually available before the end of the reference month (e.g. the Italian survey data are released about 45 days before industrial production). Confidence indicators can provide valuable information on the evolution of the economy over this period, which is one of the reasons why they are popular (Parigi and Golinelli, 2004). In this sense, even if the confidence indicators are coincident indicators of real activity, that they are available earlier means that they are quasi-leading indicators.

A number of studies have demonstrated that confidence indicators are useful for nowcasting economic activity. Giannone, Reichlin and Small (2008) examined how key data releases in the US influenced forecasts of GDP and inflation in real time. They used a dynamic factor model together with a

Kalman filter to compute real-time forecasts on the basis of unbalanced panels (due to staggered data-release dates). The methodology reduced the dimensionality problem faced by forecasters in real-time, by assuming that comovement in the economy could be described by a few of common factors. They found that survey data were important in determining predictions, particularly for real GDP growth, although this was mainly due to their timeliness.

Girardi and Reuter (2017) evaluated the impact of new releases of financial, real and survey data (using the European Commission surveys) on nowcasting euro-area GDP in real time. They found that survey and real data improved forecast accuracy throughout the sequence of nowcasts. Confidence indicators contained predictive content even after controlling for timeliness, due to their broad sectoral coverage and forward-looking nature. Similarly, Matheson (2010) found that business survey indicators improved real-time forecasting accuracy. This was due not only to their timeliness, but also to the underlying quality of the data. The results were consistent with the literature showing that survey indicators are not only timely proxies for hard data, but also contain complementary information for understanding business cycle developments.

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

The BER BCI has occasionally been included in larger datasets in forecasting exercises. For instance, Gupta, Jurgilas and Kabundi (2010) analysed the impact of monetary policy on house price growth in South Africa using a factor augmented vector autoregression. The models were based on 241 quarterly series, including real, nominal, financial and intangible variables, such as confidence indices. Gupta and Kabundi (2011) used similar large factor models, with a large cross-section of macroeconomic time series, to forecast per capita growth, inflation, and the interest rate. Confidence indices were also included in the dataset of 267 quarterly series.

Kabundi, Nel and Ruch (2016) included the BER Consumer Confidence Index (BER CCI) and the SACCI BCI to forecast real GDP growth in South Africa in real time. They argued that the timeliness of the variables was especially important. The BER CCI and the SACCI BCI are published four and two weeks before the end of the reference quarter respectively. This implies that soft data can be useful in forecasting exercises.

In this chapter, the relationship between business confidence and real activity in South Africa is examined. An attempt is made to establish whether there is a significant positive relationship between the indicators and real GDP growth, the timing of this relationship, and whether it remains significant after taking other economic variables into account. The following section turns to the literature on uncertainty.

1.3 Uncertainty

Knight (1921) defined uncertainty as agents' "inability to forecast the likelihood of events happening." Uncertainty refers to a lack of knowledge of the set of possible outcomes and their associated probabilities, because the outcome is highly unique or complex, which makes forecasting difficult. According to this definition, uncertainty is distinct from the concept of risk, which refers to a known probability distribution of a set of outcomes (either through calculation *a priori* or from statistics of past experiences). For example, a coin toss entails risk, because there is a known probability distribution (e.g. 50% chance of heads). In contrast, the number of coins ever produced entails uncertainty, because the calculation would require estimating the distribution of all the coins minted in all countries throughout history (Bloom, 2014). While researchers occasionally refer to a mixture of risk and uncertainty (Bloom, 2014), this chapter focuses on uncertainty in the sense of a lack or predictability.

This section begins with a review of the theoretical links between uncertainty and economic outcomes. The section then turns to the empirical literature, by first discussing measurement challenges and the approaches to operationalising the definition of uncertainty, and then examining the evidence on the impact of uncertainty on economic outcomes.

1.3.1 Theory on Uncertainty and Economic Outcomes

The theoretical literature emphasises two negative and two positive channels through which uncertainty can influence economic activity. Most of the focus is on 'real options' theory, based on Bernanke (1983). Uncertainty may have economic consequences when there is a degree of irreversibility to firms' actions. Firms 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 of committing to a suboptimal project, it is rational to wait before committing to an investment (Binding and Dibiasi, 2017). Because it increases the value of waiting for new information, uncertainty delays the current rate of investment (Bernanke, 1983). Thus, the option value of waiting increases as uncertainty increases (Bloom, 2014).

This theory has led to the idea of a 'wait-and-see' effect (Bloom, 2009). If a firm faces large fixed adjustment costs,[2] higher uncertainty about future demand makes new investments and hiring less attractive. Firms try to minimise the number of times this fixed adjustment cost must be paid. When the future is uncertain, in the sense that demand could be either very high or low, it makes sense to wait until the uncertainty has been resolved (Bachmann, Elstner and Sims, 2013). Facing a more uncertain environment, firms delay investment and hiring, i.e. they 'wait and see' how the future will unfold, which leads to a decrease in economic activity. As the future unfolds, there is pent-up demand for capital and labour. Firms are closer to their adjustment triggers in subsequent periods, leading to a rebound and even an overshoot in economic activity. Thus, the initial decrease is followed by a swift recovery and overshoot in economic activity (Bachmann, Elstner and Sims, 2013).

Uncertainty can also negatively affect economic activity through risk aversion and risk premia. If investors are risk averse, higher uncertainty increases risk premia, by increasing the probability of default (Redl, 2015). The accompanying increase in borrowing costs can reduce growth, as highlighted in studies of uncertainty under financial constraints (summarised in Bloom (2014) and Bachmann, Elstner and Sims (2013)). In models where agents have pessimistic beliefs, and uncertainty about the future is too high to form a probability distribution, agents act as though the

[2] For capital, these costs can be both physical (equipment may have been damaged in installation and removal) and financial (discounts for used goods). For labour, adjustment costs include recruitment, search frictions, training, and severance pay.

worst outcomes will occur (so-called ambiguity aversion). As uncertainty increases and the range of possible outcomes increases, the worst possible outcome becomes worse, leading agents to decrease investment and hiring. In contrast, if agents are optimistic (they assume the best case), uncertainty can have a positive impact on activity (Bloom, 2014).

Bloom (2014) also referred to two other channels through which uncertainty can have a positive effect on economic activity. The 'growth options' argument is based on the idea that uncertainty can create call option effects, whereby uncertainty may increase investment if the size of the potential prize increases. This is due to the potential for an increase in upside gains, while the downside loss is limited to initial sunk costs, leading to an increase in expected investment returns (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 double production if prices increase, and halve production if prices decrease, it should desire a mean-preserving increase in uncertainty. In effect, the firm can partly insure against bad outcomes by contracting and can exploit good outcomes by expanding. For this mechanism to work, firms need to be able to expand or contract easily in response to good or bad outcomes. Bloom (2014) argued that this effect is not very strong in the short run because of adjustment costs, but may be more powerful in the medium to long run.

Bonciani and Van Roye (2016) argued that in a general equilibrium framework, these 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 interest rate. They argue that this is the most important reason why many studies 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.

The theoretical literature therefore sets out potential channels through which uncertainty may have a positive or negative impact on economic activity. It then becomes an empirical question to determine the direction and significance of the impact. The following section provides a review of the empirical literature on uncertainty.

1.3.2 Empirical Findings

The recent surge in research on uncertainty has been driven by the idea that uncertainty increased during the financial crisis, and its potential 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). Although the majority of studies seems to find that uncertainty indicators are at least negatively related to real economic activity, the findings have not been conclusive. The inconclusive findings may be due to the two main challenges when it comes to empirical work on uncertainty: how to construct proxies for uncertainty and how to distinguish a separate causal impact of uncertainty.

1.3.2.1 Measuring uncertainty

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. A wide range of proxies for uncertainty have been proposed in the literature. These proxies can be grouped into five major categories, depending on the nature of the data used for their construction (Bloom, 2014). All proxies for uncertainty measure a specific type of uncertainty, and have strengths and weaknesses.

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, and exchange rates. The rationale is that more volatile series are more difficult to forecast, and are associated with a greater degree of uncertainty (Bloom, 2014). Bloom (2009), Bonciani and Van Roye (2016) and Leduc and Liu (2016), for instance, used stock market volatility as a proxy for uncertainty. A popular proxy is the Chicago Board Options Exchange Market Volatility Index (VIX), which focuses on the implied volatility of the S&P 500 Index. It reflects the dispersion of market participants' estimates of future stock prices, as measured by the implied volatility 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 Reuter, 2017).

The second category uses new information to construct uncertainty indicators. The most prominent examples are proxies based on references to 'uncertainty' in the media. Baker, Bloom and Davis (2015) and Baker, Bloom and Davis (2016), for instance, developed economic policy uncertainty indices based on the frequency of references to policy uncertainty in newspapers. Baker, Bloom and Davis (2015) combined this text mining measure with disagreement among forecasters on future government purchases and inflation, and the number of tax code provisions about to expire to create an overall indicator. One criticism is that the selection of newspapers and search terms entails a certain degree of subjectivity (Girardi and Reuter, 2017).

The third category is derived from the disagreement among professional forecasters. The rationale is that a larger dispersion of opinions about the future indicates 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, industrial production, investment, output, prices and interest rates in Germany. The downside is that the factors influencing a limited set of professional forecasters might differ from those influencing producers and consumers (Girardi and Reuter, 2017).

The fourth category uses the responses from business and consumer surveys. Bachmann, Elstner and Sims (2013), for instance, 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 *et al.* (2015) used squared forecast errors to construct uncertainty indicators for Turkey. Girardi and Reuter (2017) derived indicators of dispersion from the aggregated responses on multiple forward-looking questions. Leduc and Liu (2016) also used a survey-based proxy for uncertainty, measured as the fraction of respondents who listed uncertainty as a factor limiting their spending plans. 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 Reuter, 2017).

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 of their indicator is that it is an *ex post* measure, which requires the actual outcome of the forecasted time series before computing the indicator (Girardi and Reuter, 2017).

A few studies have constructed proxies for uncertainty in the South African context. Redl (2015) constructed an index of uncertainty for South Africa, based on disagreement among professional forecasters, the number of newspaper articles that mentioned economic uncertainty in South Africa, and references to uncertainty in the SARB's Quarterly Review.

Hlatshwayo and Saxegaard (2016) created a measure for South African economic policy uncertainty, by looking at 'news chatter' in the media, similar to the method used in Baker, Bloom and Davis (2016). They created both economic policy and political uncertainty indices at the sectoral and aggregate level, by counting the number of articles that matched specific search algorithms. Aggregate economic uncertainty, for example, was measured by counting 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 the indices were standardised. McClean (2015) created a similar news-based index for aggregate South African policy uncertainty. He found a moderate correlation between this index, the South African Volatility Index (SAVI) and 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. 'Realizations' of survey expectations was derived from changes in survey expectations in period $t-1$, compared with survey realisations in period t. They found a negative relationship between 'Volatility' and 'Realizations' for responses relating to business conditions, production, sales, fixed investment and prices. Hart (2015) also used the BER's manufacturing sector survey to create dispersion measures of uncertainty, similar to the method used in Bachmann, Elstner and Sims (2010).

Recently, North-West University (2016) created a policy uncertainty index for South Africa. The index has three components: the frequency of references to economic policy uncertainty in leading publications, expert opinions drawn from leading private sector economists, and responses from the BER manufacturing survey on whether the political climate is a constraint to doing business. This index is only available from July 2015.

None of these studies has fully exploited the information contained in the BER business tendency surveys. This chapter explores aggregation methods to try to improve on the existing measures of uncertainty for South Africa, using the microeconomic data from BER business tendency surveys.

1.3.2.2 The impact of uncertainty

The majority of studies seems to find at least a negative relationship between uncertainty proxies and economic activity, although this does not necessarily imply causality. In the literature three approaches have been taken to identify the impact of uncertainty on activity (Bloom, 2014). The first approach uses structural models to identify the potential impact of uncertainty shocks. The second approach relies on timing, typically in a VAR framework, by estimating the movements in economic activity that follow changes in uncertainty. The third approach exploits natural experiments such as exchange rate movements, disasters, and political coups.

In a number of papers, structural models (i.e. DSGE models) have been used to investigate potential mechanisms through which uncertainty may 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 decrease and subsequent rebound in aggregate output and employment predicted by the 'wait-and-see' effect.

This simulated impact was compared with VAR estimations on actual data, using stock market volatility as a proxy for uncertainty. The results matched in both magnitude and timing, with a shock to uncertainty generating a decrease and then an overshoot in employment and production.

Bloom, Bond and Van Reenen (2007) developed a model of firms' investment decisions to show that, with partial irreversibility, the impact of a firm-level demand shock on investment tends to be weaker for firms that are subject to higher uncertainty. They found evidence of more cautious investment behaviour for firms subject to higher uncertainty. Leduc and Liu (2016) used a structural model with nominal rigidities and search frictions to show the mechanism through which uncertainty could produce large economic effects. Their empirical model found that uncertainty shocks resembled aggregate demand shocks, reducing investment, short-term interest rates and inflation, and increasing credit spreads and unemployment. Bonciani and Van Roye (2016) investigated the impact of uncertainty under financial frictions with a structural model. They found that higher uncertainty reduced activity, and that the impact 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 (e.g. Arslan *et al.*, 2015; and Jurado, Ludvigson and Ng, 2015; Baker, Bloom and Davis, 2016; Girardi and Reuter, 2017). The results were generally similar to Bloom (2009), with a positive shock to uncertainty followed by a significant decrease in output, investment and employment.

Bachmann, Elstner and Sims (2010) found that innovations to their survey-based uncertainty indicators had prolonged 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, it did not have a 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 positive shocks to uncertainty were associated with a significant decrease in production and employment in both Germany and the US. German production declined and rebounded relatively quickly following an increase in uncertainty, while the response of US output was protracted, with limited evidence of a rebound. The US results suggest that some of the other mechanisms proposed in the literature, such as financial frictions may be important.

A few studies have investigated the interaction of uncertainty and these financial frictions. Popescu and Smets (2010), for instance, argued that once a measure of financial stress is included in the regressions, the independent role of uncertainty shocks becomes minimal. They found that the real effects of financial risk premia were larger and more persistent than uncertainty effects. Caldara *et al.* (2016) found that uncertainty shocks had a significant negative impact on both financial conditions and real economic activity. Their results suggested that increases in uncertainty associated with tighter financial conditions had a particularly large negative effect on real economic activity.

Other studies have exploited natural experiments such as disasters, political coups, and 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 (2017) showed how different uncertainty indicators reacted to an 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 relative to firms that were unaffected. However, once they controlled for the degree of irreversibility of firm investment, the relationship was no longer significant.

There is relatively little evidence on the impact of uncertainty on economic outcomes in South Africa. Developing countries, such as South Africa, tend to experience higher uncertainty because they tend to have less-diversified economies, which are more exposed to price and output fluctuations of volatile goods such as commodities (Bloom, 2014). Developing countries tend to have more political shocks and often have less effective stabilisation policies. Given that developing countries experience higher levels of uncertainty, it is possible that fluctuations in uncertainty have a more pronounced impact on output.

Redl (2015) argued that analysing uncertainty in developing countries could help to distinguish between the effects of financial and uncertainty shocks. During the Great Recession, many developing countries experienced high uncertainty, while not undergoing the same levels of financial stress as developed countries. He found that an increase in uncertainty in South Africa was associated with subsequent decreases in output, investment, employment, and asset prices. The results were robust to the inclusion of consumer confidence and credit spreads as a measure of financial stress, although the sizes of the responses were moderated.

Hlatshwayo and Saxegaard (2016) explored the role of policy uncertainty in South Africa 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 real effective exchange rate and had short- and long-run effects on export performance. A measure of competitiveness that adjusted for uncertainty and supply-side constraints outperformed the real effective exchange rate in tracking export performance. Similarly, Boshoff (2008) argued that developments in the Rand did not translate into business cycle movements in the South African economy, and that a weaker exchange rate was less likely to boost either foreign investment or export performance in the face of regulatory uncertainty.

Hart (2015) investigated the relationship between sentiment and economic activity in the South African manufacturing sector from 2001Q2 to 2014Q2. The study closely followed Bachmann, Elstner and Sims (2010), which also measured uncertainty in the manufacturing sector using business survey data. A VAR framework was used to estimate the impact of confidence and uncertainty on investment, production and employment in the South African manufacturing sector. None of the uncertainty measures were found to be significant, possibly due to the limited sample period.

In this chapter, the relationship between uncertainty and real activity in South Africa is examined, using standard agnostic econometric methods (VARs). In the following section the BER business tendency surveys used to create the sentiment indicators are discussed.

1.4 Data: Business Tendency Surveys

Business tendency surveys are conducted to obtain qualitative information that is useful in monitoring the current business situation and in forecasting developments in the business cycle. This is reflected in the extensive use of confidence measures as leading indicators of the business cycle (Organisation for Economic Co-operation and Development, 2003). Qualitative surveys often can be completed more easily and quickly than quantitative surveys. The results can be published before official statistics, which are often released with a significant delay. 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 which will then be picked up in quantitative statistics).

1.4.1 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 (Organisation for Economic Co-operation and Development, 2003).

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

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

The BER makes no provision for firms that were not selected or did not respond during sampling, implicitly assuming that the non-participating or non-responding firms have the same distribution as the responding firms for the period. This corresponds with the 'missing at random' assumption, which is typically used internationally (European Commission, 2006). Kershoff (2015) argued that this is a reasonable assumption, given that the responses cannot vary infinitely, and the same factors influence firms in the same sector. 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 lower levels of aggregation.[3]

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

[3]The BER does not adjust individual weights for changes in the response pattern. No calibration or 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).

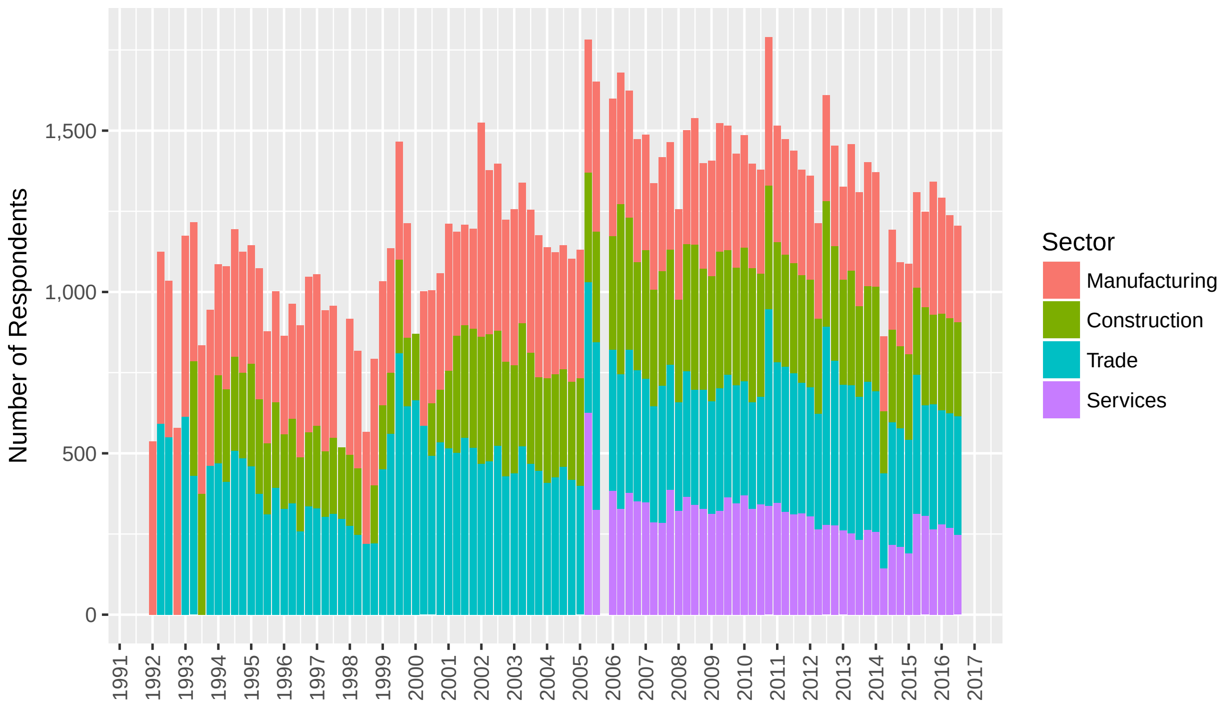

Figure 1: Number of respondents over time, by sector (1992Q1-2016Q3)

Table 3.1 reports the details of the survey data. The sample runs from 1992Q1 to 2016Q3, although the survey of the services sector started only in 2005Q2. Figure 3.1 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 119,438. All of the surveys have a few missing quarters, when the microeconomic data was lost. The overall panel sizes have remained relatively stable over time.

Table 1: Sample characteristics

Sector	Sample	Total Obs	Obs/Quarter	Response Rate	Missing Quarters
Manufacturing	1992Q1-2016Q3	36915	384.53	0.38	1997Q4,2000Q1,2005Q4
Construction	1993Q2-2016Q3	28139	312.66	0.26	1993Q4,1998Q3,2000Q2,2005Q4
Trade	1992Q2-2016Q3	40480	426.11	0.30	1992Q4,1993Q3,2005Q4
Services	2005Q2-2016Q3	13904	308.98	0.31	2005Q4
Total	1992Q1-2016Q3	119438	1218.76	0.33	2005Q4

Figure 3.2 illustrates approximate response rates for the four sectors, assuming that exactly 1,000 questionnaires were sent to firms in the manufacturing and services sectors and exactly 1,400 to the construction and trade sectors.[4] The response rates vary over time and per sector, and are relatively low by international standards (Kershoff, 2015). The total approximate response rate varied from around 20% to around 60% over the period. Response rates are around 10% higher if the inactive respondents are excluded. The response rates do not seem to follow cycles in real economic output, and exhibit insignificant correlations with real GDP growth.

[4]The response rates for the construction sector and the totals are adjusted slightly to take account of the fact that three subsectors (architects, quantity surveyors and civil engineers) were only available from 2001Q2. This adjustment was made by adding the average response rate of these subsectors.

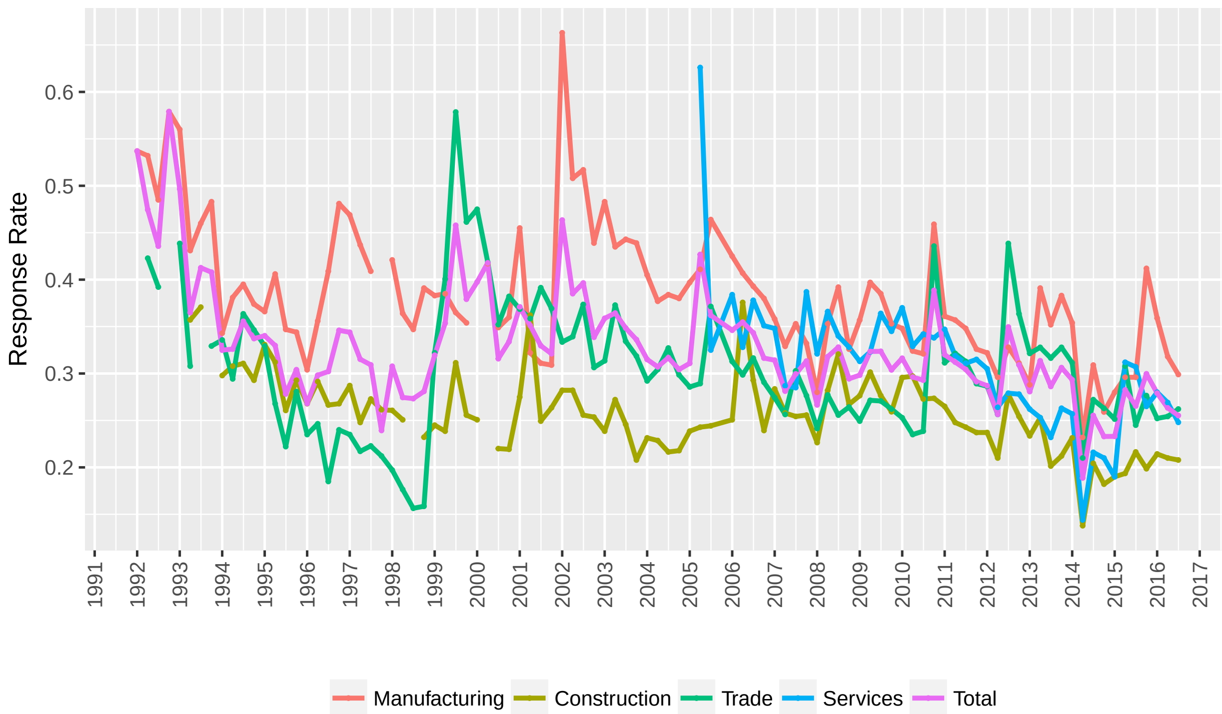

Figure 2: Approximate response rates over time per sector (1992Q1-2016Q3)

The spikes correspond to periodic recruitment drives by the BER. Every two to three years the BER removes slightly more than 25% of all respondents from the panel, because they became inactive. The BER tries to ensure that the new recruits are representative of the population, but this does mean that few firms are present throughout the sample period. While the sample of firms remains relatively stable for consecutive surveys, over longer periods the firms respond sporadically and enter and exit the sample often. Since 2005Q2, for instance, when all the data became available, only 6% of respondents replied 75% or more of the time (only 3 firms responded in all periods), 13% replied between 50% and 75% of the time, 19% replied between 25% and 50% of the time and 62% replied less than 25% of the time.

Panel sizes and response rates determine the representativeness of the sample. In order to be representative, panels have to include a minimum number of participants, which depends on the level of aggregation and the size of the population universe. The results often remain valid even if the sample size is small and the response rate relatively low. According to the Organisation for Economic Co-operation and Development (2003), even as few as 30 respondents might be sufficient to obtain an acceptable level of precision for each stratum. This is because the variance of responses for ordinal-scaled data based on a stable panel is lower than for quantitative data derived from independent surveys. Moreover, certain activities are dominated by a few large firms. Representativeness therefore has a smaller impact on qualitative survey results than on quantitative survey results. A panel that is not fully representative will probably produce similar results to a fully representative one (Kershoff, 2002).

The sample sizes illustrated in Figure 3.1 therefore seem adequate to uncover trends in the data. Kershoff (2002) found that the degree of representation of the BER's construction and trade panels adequately reflects the universes, taking response rates into account and comparing the composition of the survey panels with census and other official data. However, the number of participants per subsector may be too low to consider subsectors or provinces as sub-panels. The survey responses are therefore not disaggregated further into subsectors below.

In order to test whether the attrition rates of firms drive the results, a number of robustness exercises are carried out and reported in the chapter Appendix (section 3.10). The indicators are calculated by including only firms that form part of smaller, more 'stable', samples. The smaller samples include firms that only responded in consecutive surveys, firms that responded to more than half of all the surveys, and firms that responded to more than 75% of all the surveys, respectively. The indicators based on these smaller samples are similar to those for the full sample. This implies that these firms are driving the results, rather than the entry and exit patterns of firms.

1.4.2 The BER Business Confidence Indicator

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

In calculating business confidence, the most important issues are which survey questions to use and which weights to apply to the responses. The BER BCI is constructed from a specific question (Q1) that appears in all of the surveys: "Are prevailing business conditions: satisfactory, or unsatisfactory?" The BCI is the weighted percentage of respondents who rated prevailing business conditions as 'satisfactory' in a particular sector. The BCI is therefore a rating of business conditions at a specific point in time.

According to Kershoff (2000) there are two reasons for the use of this one question to construct the confidence indicator. Firstly, it is reasonable to assume that respondents who are satisfied with business conditions will have more confidence than those experiencing unsatisfactory conditions. Secondly, respondents take a variety of factors into account when rating prevailing business conditions, which solves the problem of weighting different factors (Kershoff, 2000). The Organisation for Economic Co-operation and Development (2003) argues that responses on general business conditions are usually based on a combination of factors, such as order book appraisals, expectations of interest rates, exchange rates and political developments.

In line with international best practice, all survey responses are weighted (except for the building survey). Each response is multiplied by a factor, which is calculated as the product of a firm size weight and a subsector size weight (except for the motor trade, where there are no subsectors). Each firm receives a weighting in relation to turnover, or the size of workforce in the case of manufacturing.[5] 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

[5] 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. The size weights are necessary because the economic significance of the responses should reflect the size of the firm (UN 2015).

not have access to the National Business Register and cannot calculate selection probabilities.[6] Responses are weighted by firm size and subsector size to obtain five sectoral indices: manufacturing, building contractors (other construction subsectors are omitted), retailers, wholesalers and new vehicle dealers. The BER BCI is calculated as the unweighted mean of the five sectoral indices (services are excluded altogether).

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

1.5 Methodology

This chapter builds on the BER BCI by calculating composite weighted indicators of confidence on current and expected conditions, as well as composite weighted forward-looking indicators of uncertainty, at a sectoral level and in aggregate. This section describes the methodology for calculating the sentiment indicators based on the microdata from the BER business tendency surveys.

The indicators are based on subjective survey responses, and therefore prone to bias. Tversky and Kahneman (1974) showed that agents rely on a number of heuristics, which reduce the complex tasks of assessing probabilities and predicting values to simpler judgmental operations. In general these heuristics are useful, but sometimes lead to severe and systematic biases. The heuristics and the accompanying reporting biases are important for how agents respond to subjective survey questions.

Anchoring and adjusting is one such heuristic, which entails anchoring with what is well-known, easily recalled from memory, or salient, and then adjusting from that anchor (Tversky and Kahneman, 1974). With anchoring, a respondent's view of the future is anchored in how they feel at present. Moreover, Gehlbach and Barge (2012) showed that survey respondents use anchoring and adjusting, where their response to an initial survey item provides an anchor from which they (insufficiently) adjust in answering the subsequent item, especially when adjacent items on the survey are similar. Thus, over the course of a survey, responses to adjacent item-pairs are likely to be more similar than responses to the same item-pairs in non-adjacent positions. Because the questions in the BER surveys are similar, and the questions on current conditions and those on expected conditions are adjacent, this bias may well be present. The subjective survey responses and the resulting subjective confidence and uncertainty indicators will consequently reflect this bias.

Arguably, there are three types of information contained in these survey responses (Fuhrer, 1988). The first reflects current developments or economic news, not yet reflected in currently available standard macroeconomic time series (e.g. changes in firms' inventory levels). The second type reflects forward-looking information, such as agents' probabilistic assessments of uncertain future

[6] The BER does not apply sample weights (i.e. the inverse of the probability of selection). This assumes that the probability of selection is the same for all units, which would be the case if firms were selected randomly (OECD 2003).

policy changes (e.g. impending tax legislation). The third type reflects 'animal spirits', where agents feel optimistic or pessimistic about future prospects for reasons not tied to fundamentals.

The significant correlations between the subjective survey-based indicators and real output in the literature (as well as in this chapter), suggest that the indicators capture at least one of these types of information. The first type of information anticipates data which will be released later. The second type may provide information about events that are either difficult to quantify or predict from the past (e.g. agents assessments of impending policy changes) (Fuhrer, 1988). Thus, they summarise changes in agents' beliefs about the future, i.e. their private information (Acemoglu and Scott, 1994). If agents act on animal spirits, which are reflected in survey data, the third type of information will explain subsequent economic outcomes due to self-fulfilling behaviour (Fuhrer, 1988).

When the agents respond to the questionnaires, they are most likely making an estimate that is partly based on the fundamentals (the first two types of information) and partly based on psychological factors or animal spirits, all of which probably contain biases.

To the extent that the indicators reflect psychological factors, the biases capture the psychological phenomena of confidence and uncertainty - i.e. agents' perceptions or degree of optimism about the future (confidence) and their inability to forecast future outcomes (uncertainty). If animal spirits influence behaviour, over and above fundamentals, these biased measures will determine agents' decisions to some extent and thereby might influence the business cycle. Thus, biased measures are still of interest if they reflect possibly biased psychological factors.

To the extent that the indicators summarise fundamental information, possibly in a biased way, the indicators still provide timely information on current developments, or information on expectations about events that are difficult to quantify. The proof of the usefulness of these potentially biased measures of fundamentals will be in their co-movement with output. Even if the indicators are subject to biases and measurement error, they still seem to contain useful additional information on agents' expectations that is not contained in standard macroeconomic variables (Fuhrer, 1988).

1.5.1 Confidence

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

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

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

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

where a is determined by the preferences of the agent. In this case a is the subjective benchmark or threshold that determines when conditions are 'satisfactory', and the measure of confidence simplifies to: $C_t^k = E_t f(Y_{t+k})$.

In this chapter, a distinction is made between indicators of current conditions C_t^k when $k = 0$, and indicators of expected conditions C_t^k when $k = 1$. Both the Conference Board and the University of Michigan make this distinction and report two consumer confidence indices: a current conditions component and an expectations component (Ludvigson, 2004). The confidence measure for current conditions C_t^0 is referred to as 'current', as it is reflects confidence about the current quarter (in the second month of the quarter). The confidence measure for expected conditions C_t^1 is referred to as 'expected', as it is reflects confidence about the following quarter.

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

The forward-looking questions (e.g. Q2P) all have the following format: "(Expected development in next quarter) Compared with the same quarter of a year ago, will general business conditions be: better, the same, or poorer?" As with the questions on current conditions, these questions ask whether the factor under consideration in time $t + 1$ is expected to be better, the same, or poorer, compared with $t - 3$. Responses are relative to the same quarter of the previous year, which corresponds with year-on-year growth rates.

Although the survey questions imply that seasonal adjustment is not required, a common challenge is that respondents may not use the correct reference period when answering the question (Organisation for Economic Co-operation and Development, 2003). For example, answers to the forward-looking questions may compare expected outcomes in the next quarter $t + 1$ with period t, instead of with period $t - 3$. In many cases, the time series of balances show some residual seasonality. The indicators are therefore adjusted for seasonality (United Nations, 2015). The results are similar without seasonal adjustments.

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

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

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

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

The weights are calculated as: $w_{it} = f_{it} s_{jt} / F_{jt}$, where f_{it} the firm size weight (i.e. the inner weight reflecting turnover or number of employees) for firm i at time t; s_{jt} is the subsector weight (i.e. the outer weight reflecting the share of total value added) for subsector j at time t; and $F_{jt} = \sum_{i=1}^{N} f_{it}$ is the total firm weight for subsector j at time t. These weights are equivalent to an explicit two-step

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	

weighting procedure, whereby weighted means are calculated for each subsector separately (using firm size weights), and then aggregated with the subsector weightings (United Nations, 2015). The BER uses similar weights, except that their weights equal the product of firm and subsector weights $w_{it} = f_{it}s_{jt}$, without dividing by the total firm weight for the subsector F_{jt}.

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

This chapter therefore combines the responses to a number of questions in the BER surveys to calculate composite indicators. For consistency, the composite indicators are derived from questions that are present in most of the sectoral business surveys. Table 3.2 reports the questions included in each of the sectoral surveys. These questions cover five types of variables, namely business conditions, activity (production or sales),[7] employment, profitability, and orders placed. Not all of the variables are covered in all the surveys. The measure of confidence about current conditions also include the question (Q1) on business satisfaction used to calculate the BER BCI. The composite sectoral indicators are calculated as the average of the weighted balances for the questions for each sector, as reported in Table 3.2. The results are very similar when the different questions are combined using principal components rather than averages. The sectoral indicators are then weighted by GDP share to form the overall aggregate composite indicators (United Nations, 2015).

1.5.2 Uncertainty

Following the literature (e.g. Bachmann, Elstner and Sims (2013), Arslan *et al.* (2015), and Girardi and Reuter (2017)), this section sets out the methodology for calculating three composite forward-looking indicators of uncertainty: (i) the scaled weighted cross-sectional standard deviation of forward-looking responses, (ii) the weighted cross-sectional mean of individual firm forecast errors, and (iii) the weighted cross-sectional standard deviation of firm forecast errors. The BER survey microeconomic data is particularly useful in this case, as it allows individual firm forecast errors to be calculated.

The cross-sectional standard deviation of responses to forward-looking questions (e.g. Q2P) D_t^1 at time t, is a measure of the dispersion of responses and is often used as a proxy for uncertainty. This

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

measure of dispersion is analogous to the proxy for uncertainty based on forecaster disagreement used by Baker, Bloom and Davis (2015). It may be defined as:

$$D_t^1 = \frac{1}{W_t}\sum_{i=1}^{N}(w_{it}E_t f(\Delta^4 Y_{i,t+1}) - \mu_{t+1})^2,$$

where the variables are defined in the same way as above, and $\mu_{t+1} = \frac{1}{W_t}\sum_{i=1}^{N} w_{it}E_t f(\Delta^4 Y_{i,t+1})$ is the weighted sample mean.

Bachmann, Elstner and Sims (2013) and Girardi and Reuter (2017) noted that the dispersion proxy for uncertainty described above suffers from a major weakness, in that it reflects changes in two factors other than pure uncertainty. First, time variation in the cross-sectional dispersion of responses may simply reflect firms reacting differently to aggregate shocks (i.e. heterogeneity), without uncertainty changing over time. Respondents can have legitimately different views on current and future prospects depending on their characteristics, such as their economic sector, export orientation and dependency on external funding. For instance, in an upswing phase with an appreciating currency, export-oriented firms might switch to more negative assessments, while other firms have more positive assessments. This would drive up the dispersion measure, without uncertainty necessarily increasing.

Second, time variation in dispersion may simply reflect time variation in the heterogeneity of expectations (i.e. disagreement), without uncertainty changing over time. Firms might respond differently to the survey questions because they use different information sets. Their assessments might vary widely and translate into high dispersion, without this necessarily indicating that respondents are uncertain of their assessments.

Accordingly, Girardi and Reuter (2017) suggested scaling the forward-looking dispersion measures D_t^1 in period t by the dispersion of responses to questions on current conditions D_{t+1}^0 in period $t+1$. The idea is that the possible drivers of dispersion differ between these assessments. The dispersion in the responses to forward-looking questions reflects the 'natural' degree of dispersion (from heterogeneity and disagreement), as well as uncertainty about the future. The dispersion of responses on current conditions should be less uncertain than assessments of future conditions, and should depend more on the degree to which conditions differ between respondents, i.e. heterogeneity and disagreement. This proxy therefore measures the extent of uncertainty, expressed as a share of the 'natural' dispersion. The scaling operation neutralises some of the impact of 'natural' dispersion of the responses to forward-looking questions. The scaled uncertainty indicator should at least be closer to actual uncertainty than dispersion based only on forward-looking question.

The first uncertainty indicator D_t, or 'dispersion', is the weighted cross-sectional standard deviation of forward-looking responses D_t^1 at time t, scaled by the weighted cross-sectional standard deviation of responses on current conditions D_{t+1}^0 at time $t+1$. More formally:

$$D_{t+1}^0 = \frac{1}{W_{t+1}}\sum_{i=1}^{N}(w_{it+1}E_{t+1} f(\Delta^4 Y_{i,t+1}) - \mu_{t+1})^2$$

$$D_t = \frac{D_t^1}{D_{t+1}^0}$$

One disadvantage of this indicator is that if economic conditions do not remain broadly stable between the two responses, the scaling might neutralise too much or too little of the dispersion and

Table 3: Possible forecast errors

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

artificially lower or increase the level of uncertainty. Another disadvantage is that it is an *ex post* measure, which requires the outcome at time $t+1$ before computing the indicator (Girardi and Reuter, 2017).

Following Bachmann, Elstner and Sims (2013), individual firms' forecast errors are used to estimate the other two proxies for uncertainty. 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 with the realisations for that question in period $t+1$. For instance, the survey responses to Q2P in period t are 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 of the responses to Q2A at time $t+1$ relative to $t-3$. The forecast errors $\epsilon_{i,t+1}$ in period $t+1$ may be defined as the realisations $E_{t+1}f(\Delta^4 Y_{i,t+1})$ of a specific outcome in period $t+1$ minus the expectations $E_t f(\Delta^4 Y_{i,t+1})$ in period t of that outcome in period $t+1$:

$$\epsilon_{i,t+1} = E_{t+1}f(\Delta^4 Y_{i,t+1}) - E_t f(\Delta^4 Y_{i,t+1})$$

Table 3.3 illustrates the nine possible forecast errors. For example, for a firm that expected an improvement in (i.e. better) conditions, the realisation of better conditions would be recorded as a 0 forecast error, no change as a -1 forecast error, and poorer conditions as a -2 forecast error.

Arslan *et al.* (2015) argued that firms make forecast errors because of uncertainty and that forecast errors should be treated as uncertainty. Following Arslan *et al.* (2015), the second measure of uncertainty A_t, or 'aggregate error' uncertainty, is the square of the weighted cross-sectional mean of the forecast errors made across firms in each quarter:

$$A_t = \bar{\epsilon}^2_{it+1},$$

where $\bar{\epsilon}_{it} = \frac{1}{W_t}\sum_{i=1}^{N} w_{it}\epsilon_{it}$.

Aggregate error uncertainty increases if more firms make similar and larger forecast errors. Thus, if more firms make the same forecast errors, aggregate error uncertainty will increase. If the same proportion of firms make positive and negative forecast errors, it implies zero aggregate error uncertainty. This is akin to the measure based on the mean of the absolute forecast errors proposed in Bachmann, Elstner and Sims (2013).

The third measure of uncertainty I_t, or 'idiosyncratic error' uncertainty, is the weighted cross-sectional standard deviation of the forecast errors in each quarter:

$$I_t = \frac{1}{W_{t+1}}\sum_{i=1}^{N} w_{it+1}(\epsilon_{it+1} - \bar{\epsilon}_{t+1})^2,$$

where the variables are defined in the same way as above.

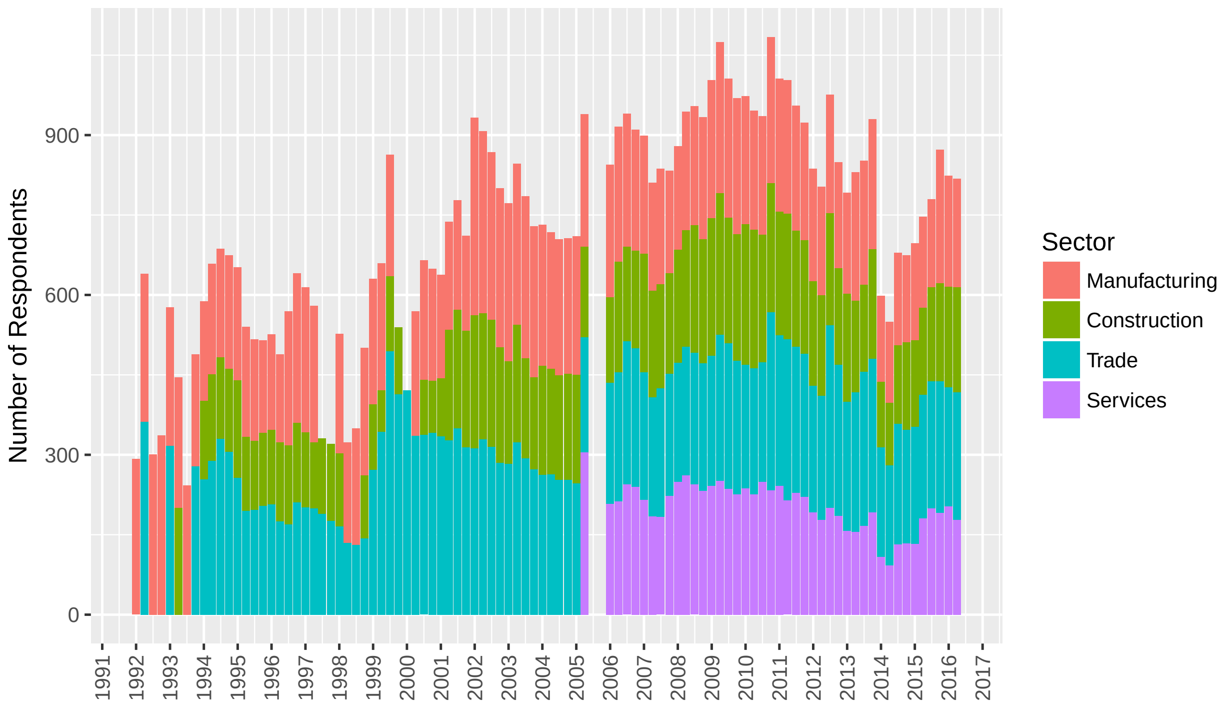

Figure 3: Sample sizes of the forecast errors, by sector (1992Q1-2016Q3)

This proxy measures how individual firms depart from the overall mean forecast error. Idiosyncratic error uncertainty increases if firms make more dispersed forecast errors. If all firms make the same forecast error, it implies zero idiosyncratic error uncertainty. This is the measure of uncertainty proposed in Bachmann, Elstner and Sims (2013).

Although these measures are based on the realised forecast errors in the next quarter $t+1$, they depend on the knowledge and level of uncertainty in the current quarter t. Thus, the mean and standard deviation of realised forecast errors at time $t+1$ constitutes uncertainty in t (Bachmann, Elstner and Sims, 2013).

The composite uncertainty indicators for each sector are then calculated as the average of the same set of survey questions reported in Table 3.2. 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 Reuter, 2017). The sectoral indicators are then aggregated with GDP shares as weights, to form the overall uncertainty indicators.

Figure 3.3 illustrates the sample sizes of the forecast errors by sector. Naturally, these sample size are smaller than the full sample because they require firms to respond in two consecutive quarters. Nevertheless, the sample sizes are still relatively large compared to the full sample, with around 725 forecast errors on average per quarter.

Similar to the case with the non-responses in the full sample, it is assumed that the firms that did not form part of this sample have the same distribution as those included. In other words, the firms that did not respond in consecutive periods have a similar distribution to those that did respond to consecutive surveys. This so-called missing-at-random assumption is common in the international

Table 4: Comparing sample characteristics in terms of firm size

Firm Size	Full Sample		Forecast Error Sample	
Category	Observations	Percentage of sample	Observations	Percentage of sample
1	25,587	21.43%	14,537	20.88%
2	15,288	12.80%	9,079	13.04%
3	18,554	15.54%	10,936	15.71%
4	13,717	11.49%	8,094	11.63%
5	14,676	12.29%	8,748	12.57%
6	9,140	7.65%	5,331	7.66%
7	6,899	5.78%	3,980	5.72%
8	6,894	5.77%	3,739	5.37%
9	8,667	7.26%	5,166	7.42%

literature when dealing with non-responses in business tendency surveys (EC 2006).

Of course, this need not necessarily be the case. Table 3.4 compares the characteristics, in terms of firm size, between the firms in the full sample and those that only form part of the forecast error sample (i.e. firms that responded in consecutive quarters). The characteristics of the two samples are similar in terms of the size of the firms. As reported in the Appendix, the results are similar when calculating the confidence and uncertainty indicators using only the smaller forecast error sample. The other measures, which do not rely on the panel structure, are therefore robust to calculating them for the more 'stable' sample.

Thus, there are three distinct proxies for business uncertainty based on the survey data: dispersion D_t, aggregate error uncertainty A_t and idiosyncratic error uncertainty I_t. Business uncertainty can come from a number of sources and may manifest itself in an array of variables (Jurado, Ludvigson and Ng, 2015). Hence, this chapter also investigates two further proxies for uncertainty, namely economic policy uncertainty and financial market uncertainty.

The economic policy uncertainty indicator is the news-based EPU index created by Hlatshwayo and Saxegaard (2016), discussed above. It is constructed by counting the number of articles that contained 3 mentions of words related to policy, economics, and uncertainty within 10 words of 'South Africa'. The absolute counts were normalised and the index was standardised.

The financial market uncertainty indicator 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 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 three months' time. It is calculated using implied volatilities obtained daily from specific Top 40 options (JSE, 2014). The SAVI is available only from June 2007. Following the literature (e.g. Bloom (2009), Valencia (2017), Bachmann, Elstner and Sims (2013) and Redl (2015)), an index of realised stock return volatility was calculated as the standard deviation of the daily JSE All Share index for each quarter. The realised volatility for the period before June 2007 is then chained to the SAVI.

This chapter therefore investigates five proxies for uncertainty. None of them is a perfect measure of an elusive and multidimensional phenomenon, but all of them may contribute to our understanding of uncertainty (Bachmann, Elstner and Sims, 2013). 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 hightened uncertainty during extreme events (Bachmann, Elstner and Sims, 2013). Moreover, survey responses are potentially biased and there may be a gap between responses and actual behaviour (Baker and Wurgler, 2007). The survey-based methods do not focus specifically on economic policy uncertainty, which captured in the EPU of Hlatshwayo and Saxegaard (2016). The SAVI captures broad uncertainty in financial markets, which is the most popular proxy in the literature, but is derived from a specific segment of firms that are publicly traded.

These five imperfect proxies can be combined to form an overall uncertainty indicator for South Africa. The indicators are combined to attempt to incorporate information from different sources of uncertainty (Leduc and Liu, 2016). This is similar to practices in the literature, where uncertainty indicators are constructed from a range of different proxies (e.g. Baker and Wurgler (2007); Baker, Bloom and Davis (2015), Redl (2015) and North-West University (2016)). The idea is to iron out the remaining idiosyncrasies by averaging the indicators to incorporate information from different sources of uncertainty. This should reduce their likelihood of signalling high uncertainty where there is none, or of failing to detect mounting uncertainty (Girardi and Reuter, 2017). Moreover, incorporating uncertainty from different sources may help to detect exceptionally high uncertainty from specific sources, e.g. from policy changes, which are not captured well by the other indicators.

In constructing their uncertainty measure, Baker and Wurgler (2007) and Baker, Bloom and Davis (2015) used a simple average of their proxies, as well as the first principal component of the series. In this chapter, the first principal component of the five standardised uncertainty proxies is used as an overall combined uncertainty measure ('combined'). A number of papers have used principal component analysis (PCA), or the related factor analysis, to reduce the dimensionality of their data (see Stock and Watson (2002) for a seminal contribution, and Gupta and Kabundi (2011), and Bosch and Ruch (2013) for South African applications). PCA is used to reduce the dimensionality of a dataset consisting of a large number of variables, while retaining as much of the variation as possible (Jolliffe, 2002). The transformation is defined in such a way that the first principal component accounts for as much of the variability in the data as possible (see Jolliffe (2002) for a complete derivation of PCA). The results presented below indicate that the combined indicator exhibits a larger correlation with movements in real output growth than any of the separate components. The results are similar for an equal-weighted overall combined uncertainty index.

1.5.3 Weighing the Survey Responses

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

Figure 3.4 to Figure 3.7 illustrate the subsector weights for each of the four main sectors: manufacturing, construction, trade and services. The weights for the manufacturing subsectors are updated periodically by the BER, based on the composition of production or sales in each subsector, as calculated by StatsSA. The subsector weights are cleaned versions of those used by the BER in calculating its Manufacturing BCI.

Subsector weights are not recorded by the BER for the construction sector. The BER Building BCI is based on the unweighted responses for contractors only. In this chapter, the relative subsector weights are set equal to the average number of respondents for each subsector over the period. The

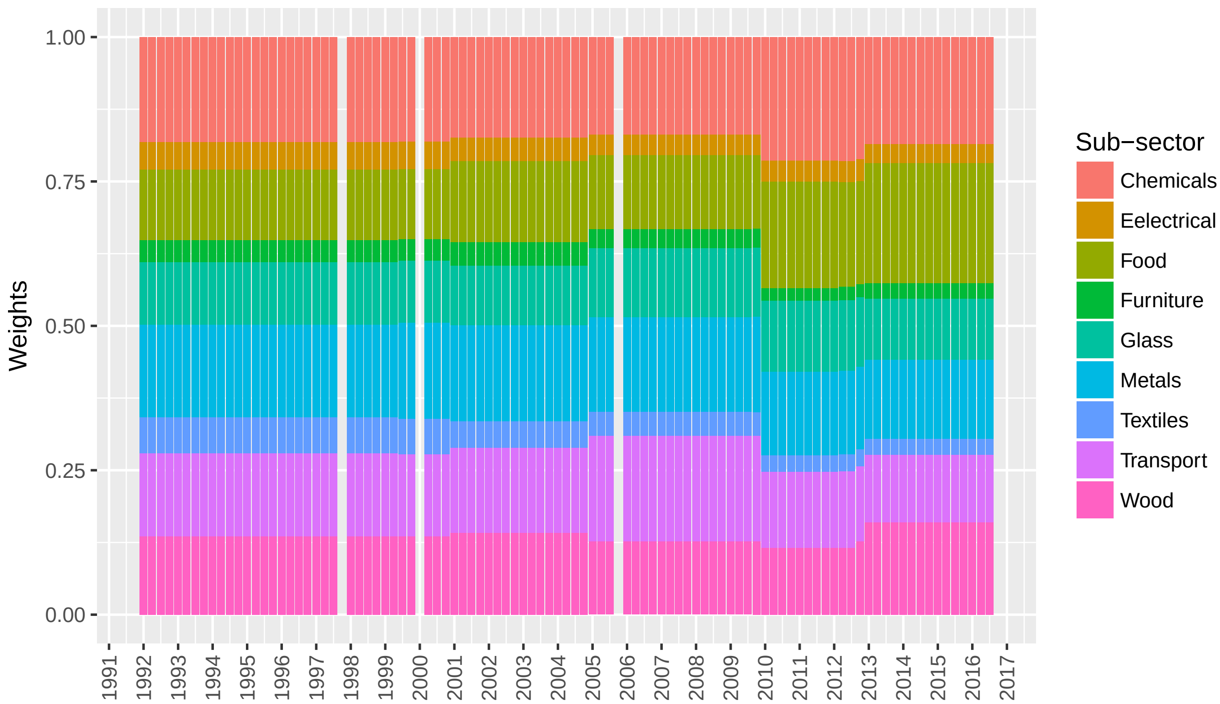

Figure 4: Subsector weights applied in the manufacturing sector

results are similar when using an equal weighting procedure. The microdata for architects, quantity surveyors and civil engineers are only available from 2001Q2.

The BER also updates the weights for the retail and wholesale subsectors periodically. The weights for these subsectors in this chapter are the same as those used by the BER in calculating its Retail and Wholesale BCIs. The BER Motor Vehicle BCI does not receive a subsector weighting. The BER assumes an equal weighting for the retail, wholesale and motor vehicle subsectors when calculating its total BCI. In this chapter, the relative weights are set equal to the average number of respondents for each subsector over the sample period. The results are similar when using an equal weighting procedure.

Subsector weights are not recorded by the BER for the services sector and the BER does not publish a Services BCI. In this chapter, the weights are set equal to the average number of respondents for each subsector over the sample period, although the results are similar when using equal weights.

Figure 3.8 illustrates the GDP share weights that are used in aggregating the four sector indicators to calculate the aggregate indicators. The BER BCI, in contrast, is a simple equal weighted average of the sectoral indicators for manufacturing, contractors, retail, wholesale, and motor vehicles.

Naturally, there are other ways to weigh the responses, but experience has shown that the balances are not very sensitive to the choice of weighting procedure (Organisation for Economic Co-operation and Development, 2003). Indeed, in this case the specific weighting procedure turns out to have little impact on the confidence indices. 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 to the weighted versions. The application of the BER weights also provides similar results.

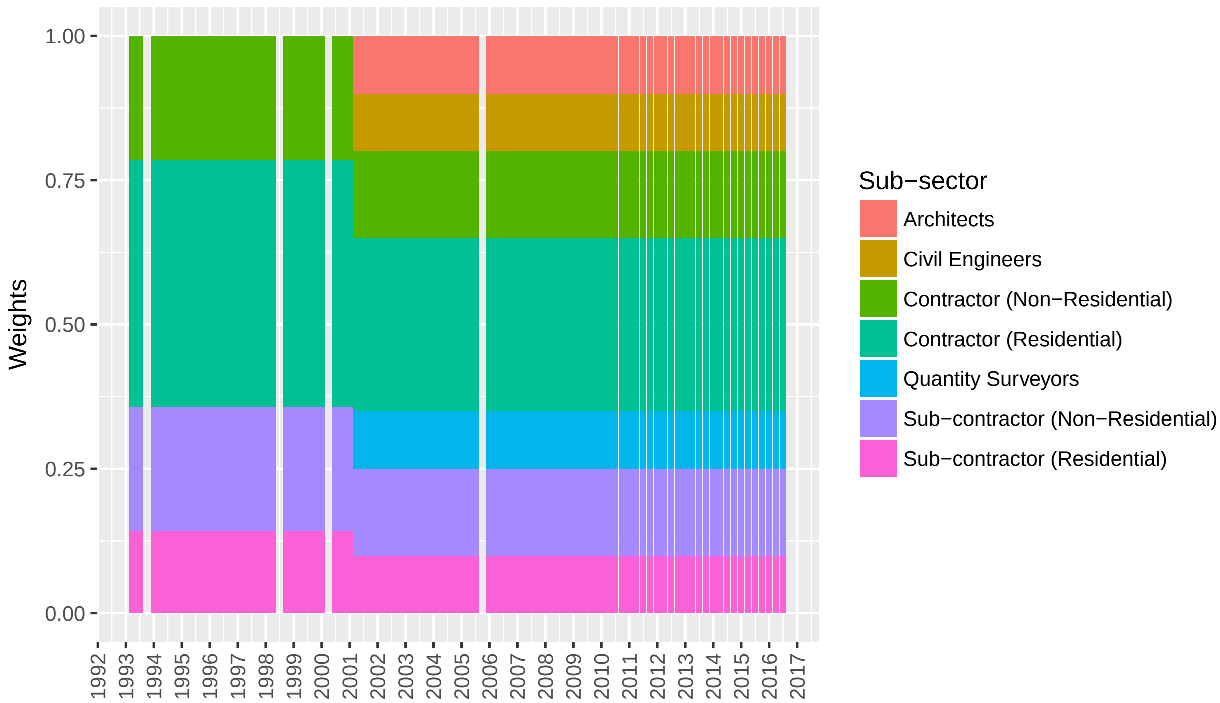

Figure 5: Subsector weights applied in the construction sector

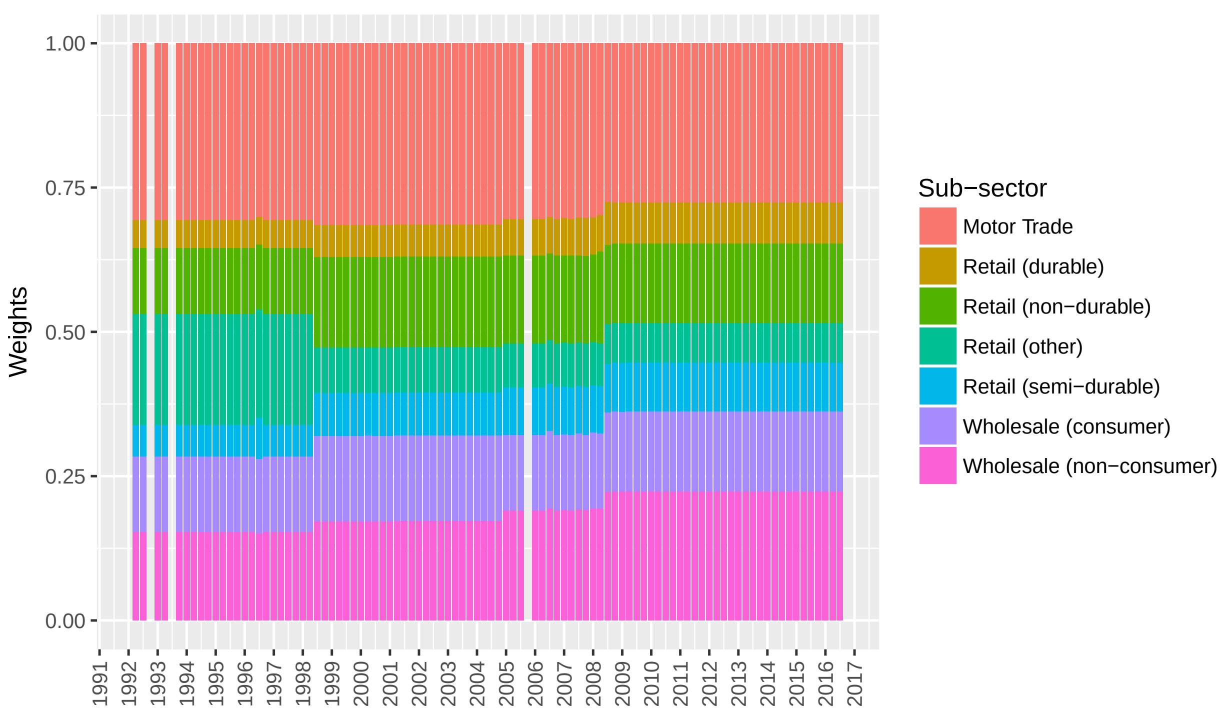

Figure 6: Subsector weights applied in the trade sector

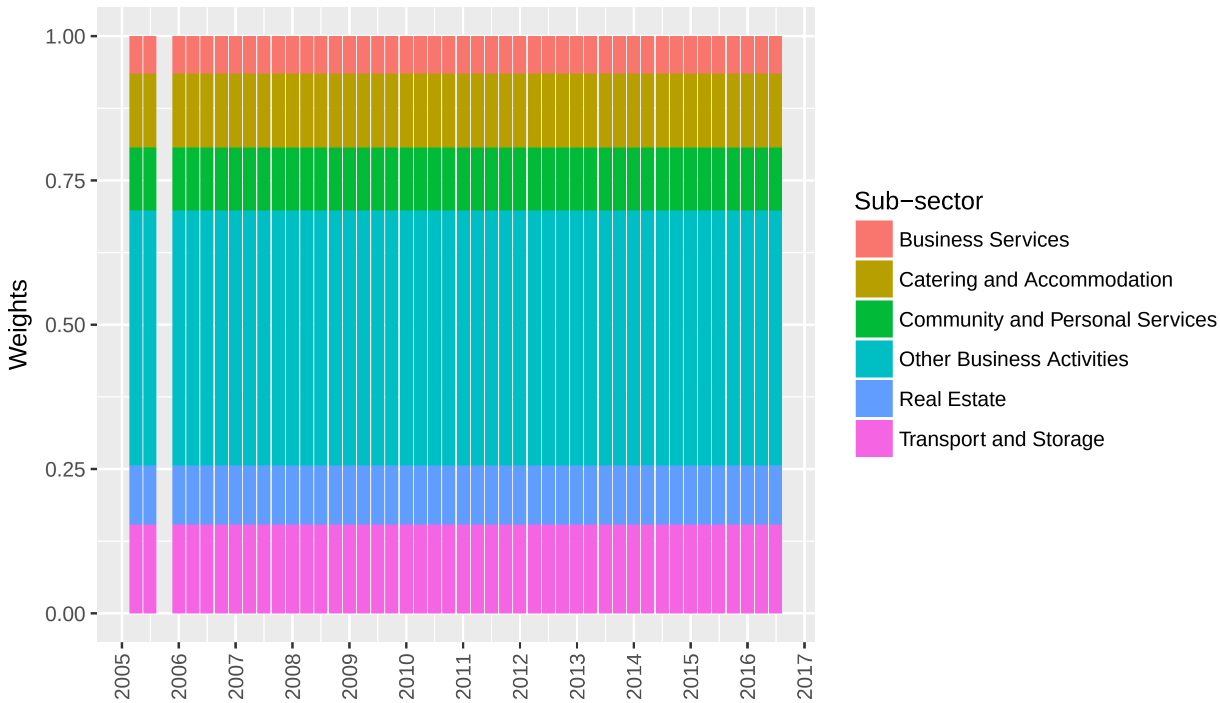

Figure 7: Subsector weights applied in the services sector

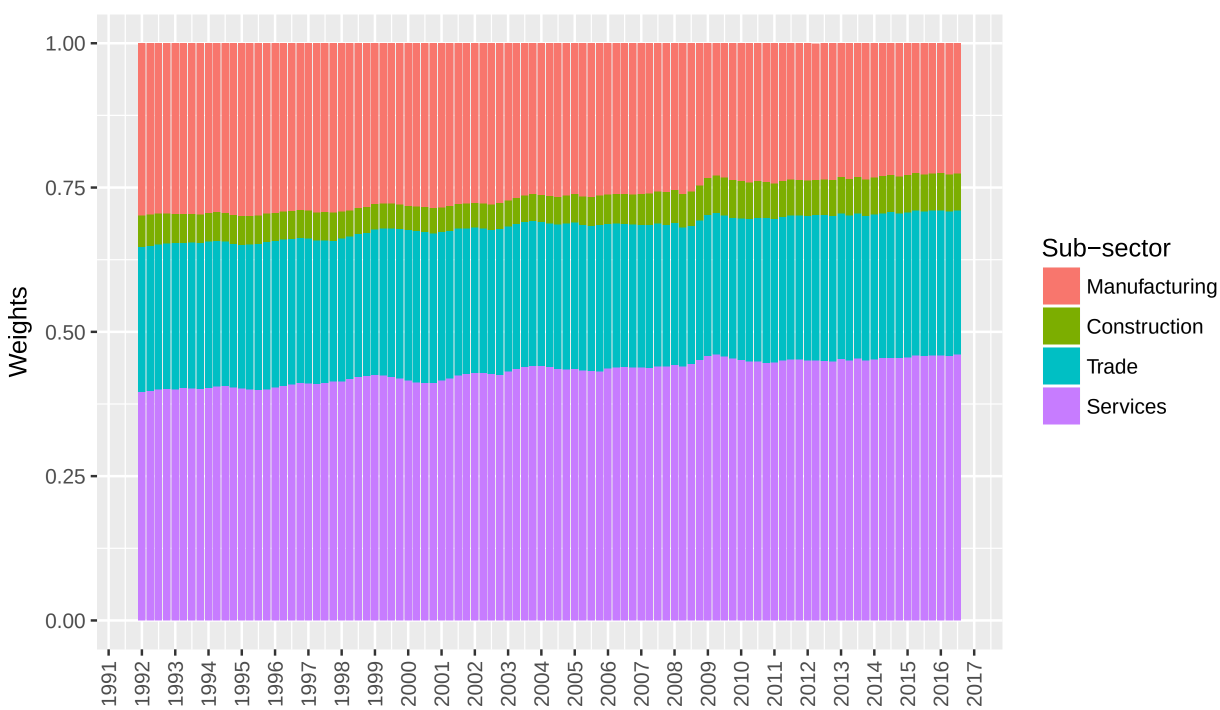

Figure 8: GDP share weights applied to the main sectors

The specific weighting procedure adopted therefore does not significantly alter the results.

This confirms the findings by Kershoff (2015), who tested alternative weighting procedures: 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 a two-step weighting procedure; the inclusion of latecomers to increase the number of responses; and the use of different sector size weights for export variables. The findings showed that the balance statistics were not sensitive to the use of alternative weighting procedures.

1.6 Results: Confidence

This section presents the composite sectoral and aggregate business confidence indicators for South Africa. Simple linear interpolation is used for the few missing quarters. The validity of the indicators is assessed by comparing them with events that were thought to coincide with large changes in confidence, as well as with existing measures of confidence for South Africa. The indicators are then evaluated according to their comovement with real GDP growth (i.e. their tracking record), to assess whether they improve on the existing indicators of confidence.

1.6.1 Confidence Indicators

Figure 3.9 illustrates the weighted sectoral confidence indicators for current conditions and expected conditions. The indicators appear to capture cyclical movements in the sectors. In general, they display an increase in the early 1990s until just after the first Democratic Elections in 1994Q2. They show a sustained decrease from 1995 into the recession of 1997-1998, associated with the East Asian and Russian crises. After troughs around the start of 1999, the indicators increase up to the global financial crisis at the end of 2007. During this extended upswing phase, the manufacturing and trade sectors reflect the two ambiguous periods in 2001 and 2003, when contractions in the SARB leading and coincident indicators obliged an evaluation of possible reference turning points (Venter, 2005). The construction sector exhibited a particularly strong and sustained increase in confidence during this upswing phase, possibly due to the construction projects associated with hosting the FIFA World Cup in 2010.

The global financial crisis was followed by a large decline in the indicators for all of the sectors, which continued into the subsequent Great Recession. There was a relatively quick recovery in confidence in the manufacturing and trade sectors. Confidence in the construction sector showed a more gradual recovery, especially in confidence on current conditions. In the services sector, confidence on current conditions showed a slight recovery and then continued to decline, whereas confidence on expected conditions was quite erratic. The indicators for the other sectors exhibit a gradual decrease from around 2012, continuing into the downswing phase at the end of the sample period.

Figure 3.10 illustrates the weighted aggregate confidence indicators on current and expected conditions. 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 is reported in Table 3.5, below.

The indicators appear to match the different phases of the business cycle relatively well. Turning points generally coincide with the official turning points, as is discussed in more detail below. The

Figure 9: Weighted sectoral confidence indicators on current and expected conditions

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

As reported in the Appendix, the indicators are robust to calculation based on more stable samples of firms. The Appendix also illustrates confidence intervals around the aggregate and sectoral confidence indices. The confidence intervals show that the distribution of the sample means are relatively narrow, because of the large number observation in each quarter. As a consequence, the changes in the indices seem 'real' rather than statistical idiosyncrasies. The survey-based confidence indicators therefore appear to be plausible and potentially useful indicators of business confidence in South Africa.

1.6.2 Validity Tests and Evaluation

This section provides a comparison of the characteristics of the new confidence indicators to the two existing South African business confidence indices, the BER BCI and the SACCI BCI. Correlations are used to analyse the tracking record of the indicators with respect to real GDP growth. The relationships between turning points is reported, to assess their usefulness as leading indicators of the business cycle.

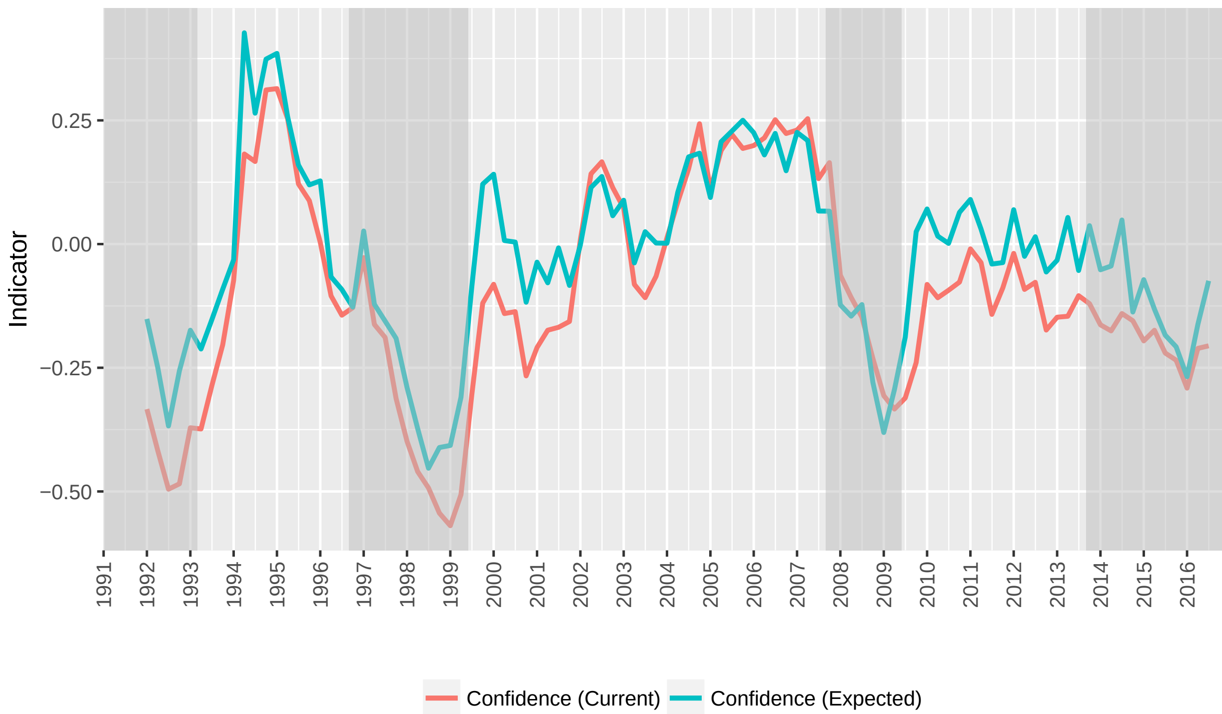

Figure 10: Weighted confidence indicators on current and expected conditions

1.6.2.1 Correlations between confidence indicators and real GDP growth

Figure 3.11 compares the confidence indicators on current and expected conditions with the BER BCI,[8] the SACCI BCI, as well as real GDP growth. Real GDP growth is calculated as annual quarter-on-quarter growth rates, e.g. 2015Q1 over 2014Q1, which corresponds to the reference period in the BER surveys. The official recessionary periods are shaded, and the indicators are standardised for plotting. The indicators appear to be strongly pro-cyclical, and follow real GDP growth closely.

Table 3.5 reports the contemporaneous correlations of the indicators and real GDP growth. SACCI

[8]The new confidence indicators differ from the BER BCI in a number of ways. First, the BER BCI is based on a single question related to satisfaction with general business conditions. The new confidence indicators are composite indicators that combine the responses to five types of variables, namely business conditions, activity (production or sales), orders placed, employment, and profitability. Second, the BER BCI excludes the services sector altogether, and excludes the other construction subsectors apart from building contractors (i.e. sub-contractors, architects, quantity surveyors, and civil engineers). The new confidence indicators include all of the available survey responses. Third, the BER BCI weighs each response with a factor, which is calculated as the product of a firm size weight and a subsector size weight, $w_{it} = f_{it}s_{jt}$, without dividing by the total firm weight for the subsector F_{jt}. In contrast, the new confidence indicators use weights, $w_{it} = f_{it}s_{jt}/F_{jt}$, which are equivalent to an explicit two-step weighting procedure, whereby weighted means are calculated for each subsector separately, and then aggregated with the subsector weightings. Fourth, the BER BCI uses exponential firm weights, which makes the series particularly volatile. The new confidence indicators use simple linear weights based on the size categories. Fifth, the BER BCI does not weigh the responses from the building contractor and motor vehicle surveys. The new confidence indicators weigh all of the sectors in the same way. Sixth, the BER BCI assumes that the five sectoral indices (manufacturing, building contractors, retailers, wholesalers and new vehicle dealers) have an equal weighting, which increases the importance of motor vehicle dealers substantially. The new confidence indicators combine the sectoral series with weights based on GDP shares to create the aggregate confidence indicators.

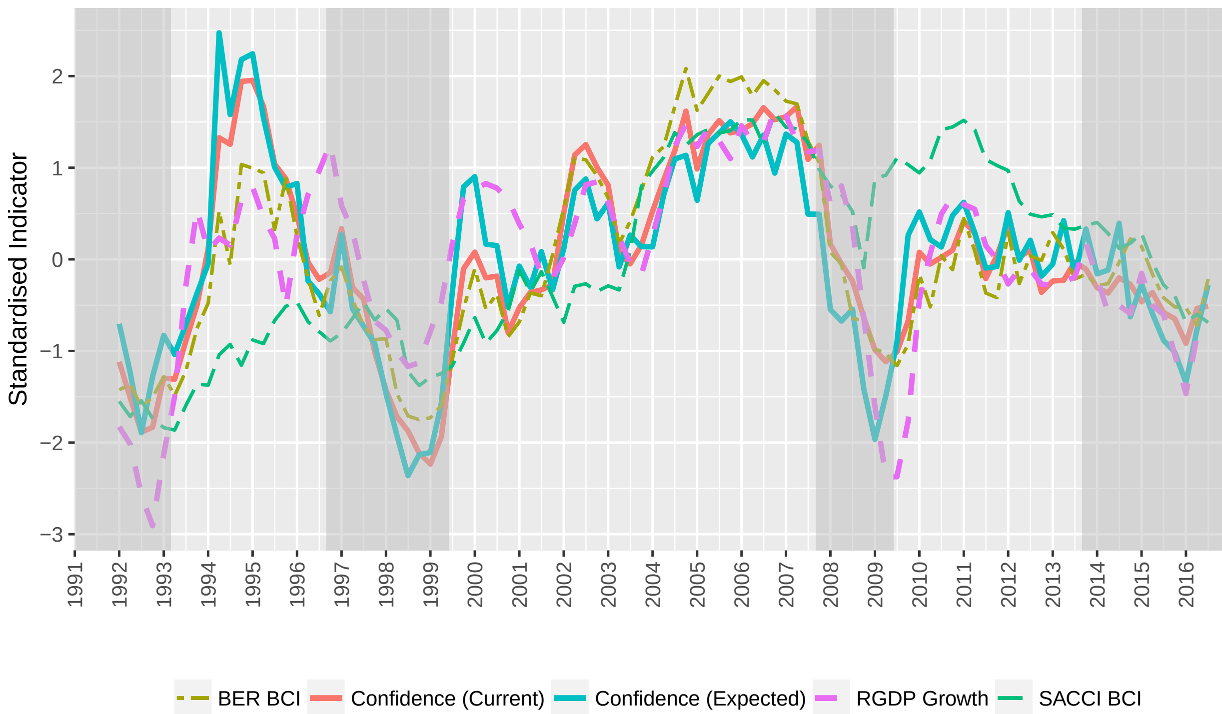

Figure 11: Confidence indicators compared to real GDP growth

BCI growth rates are used to remove unit roots and are calculated as annual quarter-on-quarter growth. All the indicators exhibit a significant positive correlation with one another and with real GDP growth. The current conditions confidence indicator has a marginally higher contemporaneous correlation with real GDP growth than the BER BCI or SACCI BCI, which are also based on current conditions. The correlation between the expected conditions confidence indicator and contemporaneous real GDP growth is also relatively high.

Table 5: Correlations between confidence indicators and real GDP growth

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

Cross-correlations can be used to illustrate the dynamic relationships between the indicators and real GDP growth. Figure 3.12 illustrates the cross-correlograms for the indicators and real GDP growth. All three survey-based measures exhibit relatively high correlations with contemporaneous and lagged GDP growth. The highest correlation coefficient between the indicators of current conditions and real GDP growth occur contemporaneously. The confidence measure of expected conditions leads GDP growth, and exhibits the highest correlation coefficient when lagged by one period. The results imply that the indicators are all potentially useful leading or quasi-leading indicators of real activity.

Figure 3.13 compares the sectoral current and expected conditions confidence indicators with the BER sectoral indicators, as well as with the corresponding real sectoral GDP growth rates.

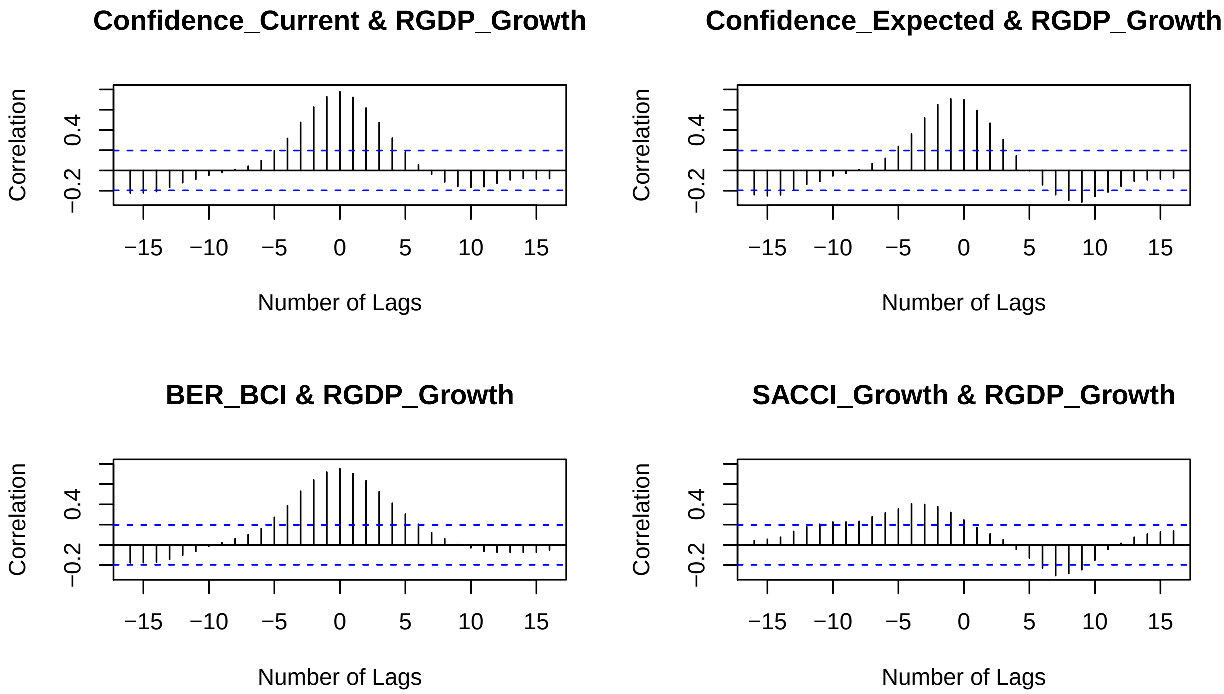

Figure 12: Cross-correlograms of the confidence indicators and real GDP growth

The indicators capture cyclical movements in real output over the period. Table 3.6 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 sectoral GDP growth rates. For the most part, the current conditions confidence indicators exhibit the highest correlation with the reference series. In this sense, they are an improvement on existing confidence indicators. The exception is the construction sector, where the BER Building BCI has the highest correlation. This is peculiar, as the BER Building BCI includes only building contractors.

Table 6: Correlations between sectoral confidence and real sectoral GDP growth

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

Figure 3.14 illustrates the cross-correlograms for the manufacturing indicators and real GDP growth in the manufacturing sector. The results are similar to the aggregate results. Again, all three survey-based measures exhibit relatively high correlations with contemporaneous and lagged GDP growth. The expected conditions confidence measure leads real GDP growth. The cross-correlograms for the other sectors are very similar (not shown), except for the services sector, where the expected

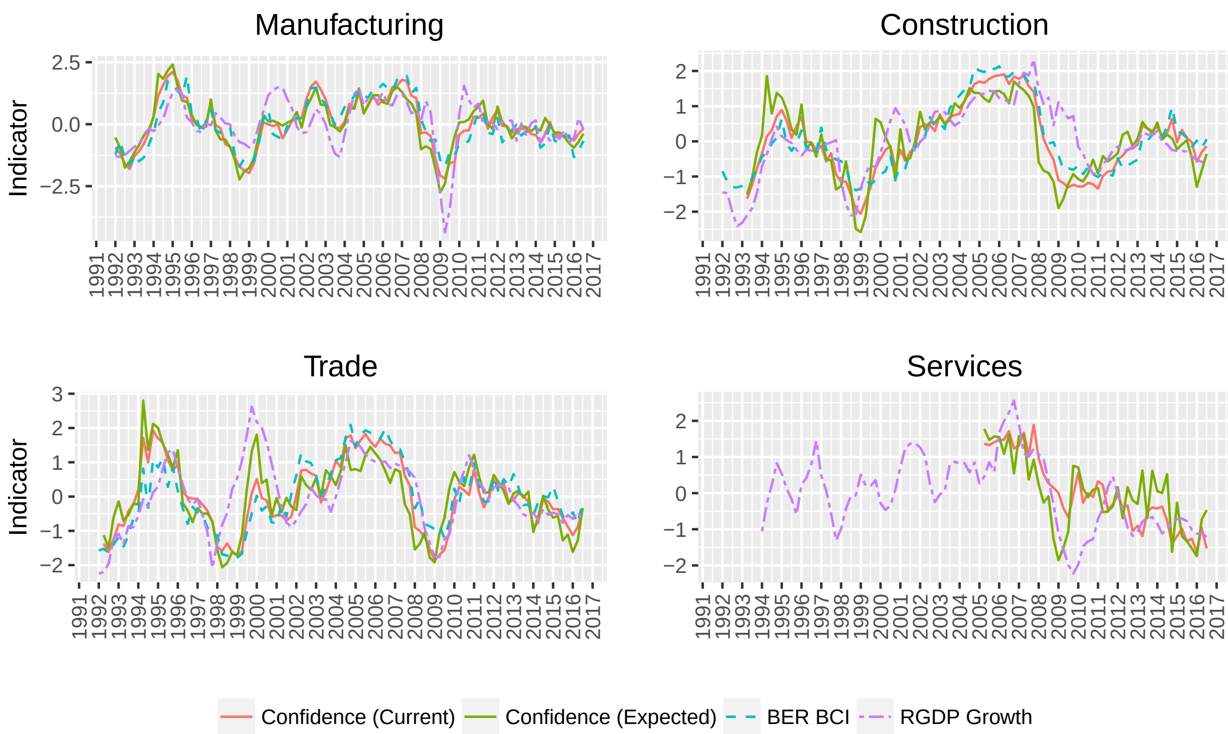

Figure 13: Sectoral confidence indicators compared to real sectoral GDP growth

conditions confidence measure has an even longer leading relationship with real GDP growth.

1.6.2.2 Turning points

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

The turning points in the indicators are determined where the indicators breach the threshold of zero, i.e. they indicate an upswing when they are positive and a recession when they are negative. The two new indicators and the BER BCI are standardised, as their means are below zero over the sample period, and the SACCI BCI enters in growth rates. Censoring rules are used to ensure that phases and cycles have a minimum duration, similar to those used in the so-called Bry-Boschan method (Bry and Boschan, 1971). Following the suggestion of Harding and Pagan (2002), who developed a variant of this method for dealing with quarterly data (the BBQ method), a censoring rule based on a minimum of two quarters for each phase and five quarters for a full cycle is applied.

The resulting phases are illustrated in Figure 3.15, with the recessionary periods shaded. The top panel of each graph illustrates the turning points of the confidence indices, while the bottom panel of each graph shows the official SARB reference turning points. The sample period includes three upswing phases and four downswing phases. In addition, in 2001 and 2003 the SARB indicators

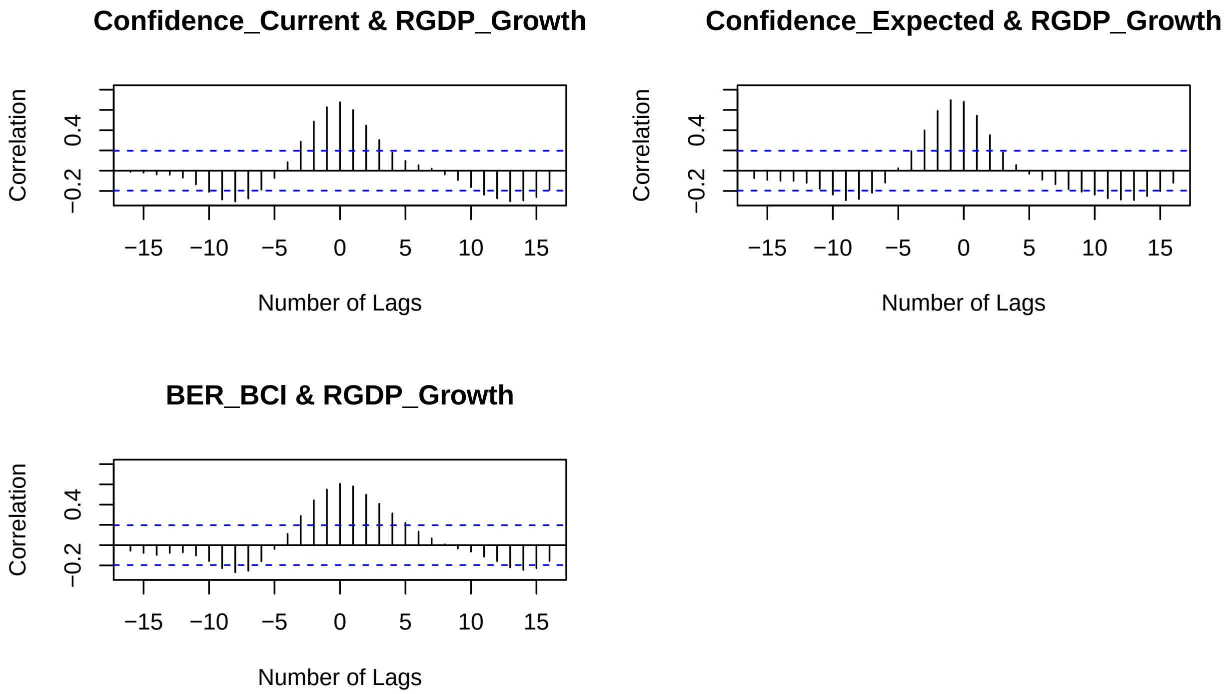

Figure 14: Cross-correlograms of the indicators and real GDP growth in the manufacturing sector

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 algorithm identifies four recessionary periods in the current conditions confidence indicator and five in the expected conditions confidence indicator. These correspond to the official downswing phases, with the additional downswing phase during the semi-recession in 2001. The turning points in the BER and SACCI BCIs are similar to those for the new confidence indicators. There is some ambiguity towards the latter part of the sample period, as the expected conditions confidence indicator and the BER BCI hover around the zero threshold. On the whole the phases identified with the indicators are longer in duration than the official phases. The indicators mostly exhibit peaks before the official peak dates, by as many as 10 quarters before the official peak. The indicators exhibit troughs concurrent with or after the three official trough dates. The indicators therefore seem to reflect the official business cycle turning points relatively well.

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

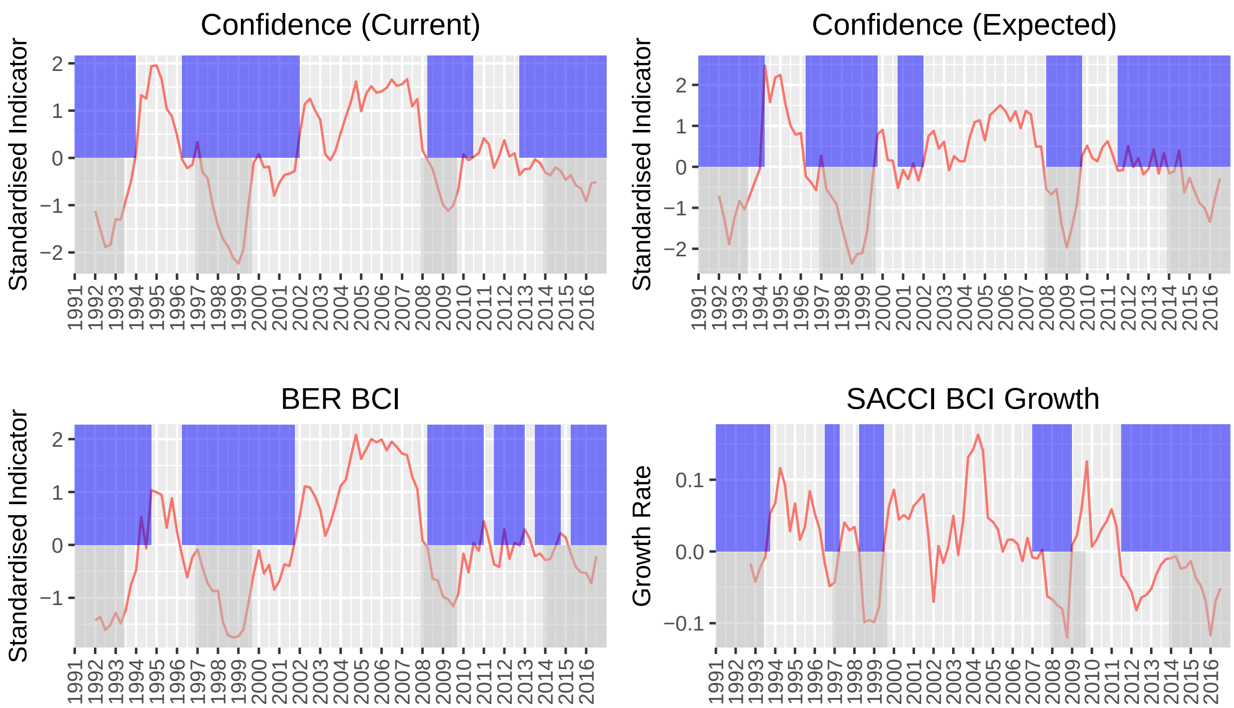

Figure 15: Confidence indicator turning points compared to the official SARB turning points

Table 7: Concordance statistics with the SARB business cycle

	Confidence (Current)	**Confidence (Expected)**	**BER BCI**	**SACCI BCI Growth**
lead=3	0.60	0.62*	0.47	0.72**
lead=2	0.65*	0.67**	0.54	0.75***
lead=1	0.68**	0.70***	0.59*	0.76***
lead/lag=0	0.71***	0.73***	0.62**	0.75***
lag=1	0.72***	0.74***	0.63***	0.70***
lag=2	0.73***	0.69***	0.64***	0.65***
lag=3	0.72***	0.64***	0.63***	0.6**

Table 3.7 reports the concordance statistics for the phases of the indicator variables, compared with the official SARB reference turning points. The indicators all exhibit significant concordance with the official SARB business cycle. The three survey-based indicators have the highest concordance statistic with the official SARB cycle when they are lagged by one or two quarters, but the contemporaneous concordance statistics are all significant.

The indicators therefore seem to reflect the official business cycle turning points relatively well, and provided advance warning especially of the official peaks. The results suggest that the confidence indicators are potentially useful leading indicators of the business cycle. However, the false positives and ambiguous periods imply that the indicators should be used in conjunction with other series when identifying turning points, as in Laubscher (2014). As more microeconomic data from the BER's business tendency surveys become available, the analysis could be expanded by analysing the cyclical properties of the indicators in terms of duration, amplitude and steepness.

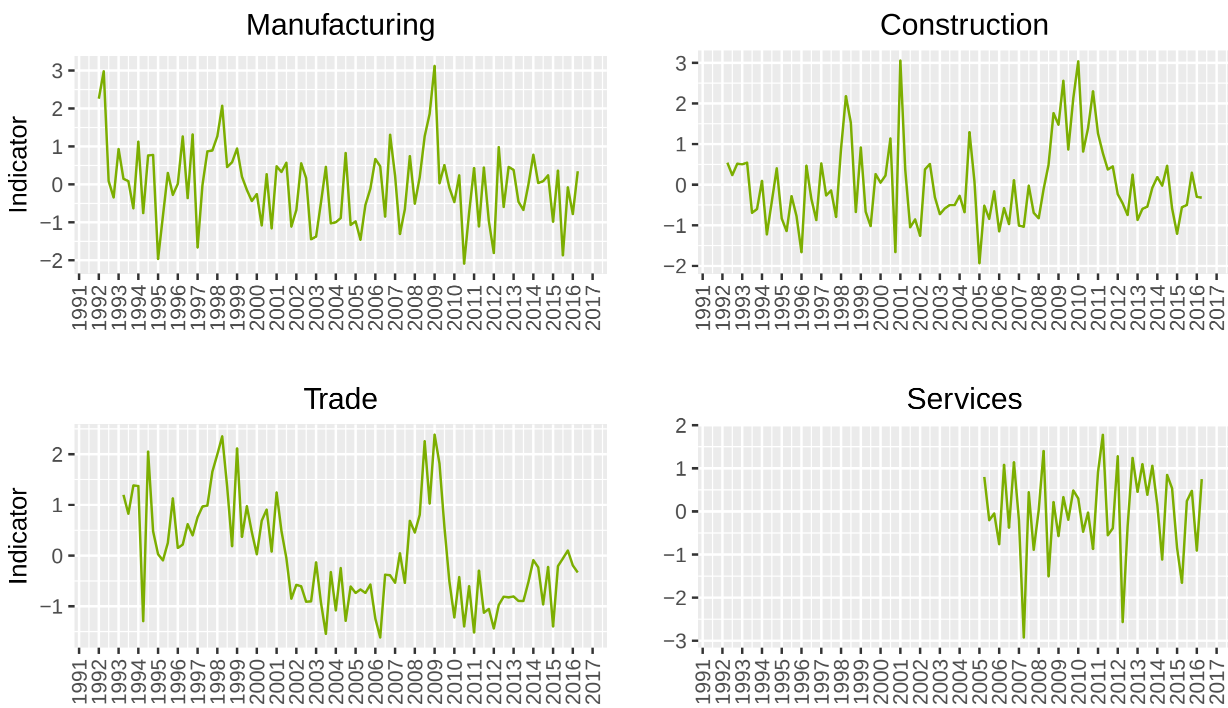

Figure 16: Weighted sectoral indicators of dispersion

1.7 Results: Uncertainty

This section presents the composite sectoral and aggregate indicators of uncertainty for South Africa. Simple linear interpolation is used for the few missing quarters and all the indicators are standardised. The validity of the indicators is evaluated by assessing whether large changes coincided with events that may have induced uncertainty, as well as by comparing them with existing measures for South Africa. The indicators are then evaluated in terms of their comovement with real GDP growth, to assess whether they improve on the existing indicators of uncertainty. An overall uncertainty indicator is then created, which tries to combine the information in all of the indicators.

1.7.1 Uncertainty Indicators

Figure 3.16 illustrates the weighted sectoral indicators of uncertainty based on dispersion. These indicators are quite volatile by construction (Girardi and Reuter, 2017). The indicators of dispersion for the manufacturing, construction and trade sectors spike during the 1997-1998 recession, associated with the East Asian and Russian crises. In those three sectors the indicators also increased in the recessionary period following the global financial crisis. The dispersion indicator for the manufacturing sector also exhibits a spike at the beginning of the period during the Democratic transition. The dispersion indicator for the services sector is particularly volatile and does not exhibit the large increase during the Great Recession which is present in the indicators for the other sectors.

Figure 3.17 illustrates the weighted sectoral indicators of aggregate error uncertainty. The indicators

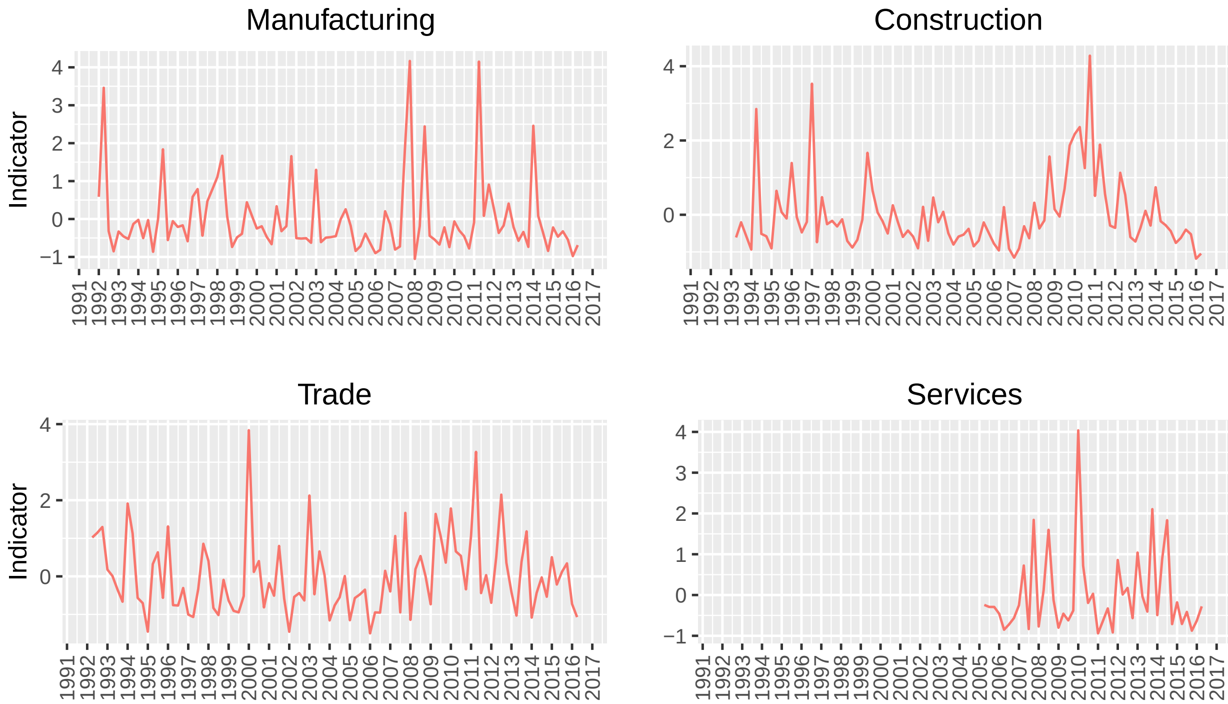

Figure 17: Weighted sectoral indicators of aggregate forecast error uncertainty

in the manufacturing, construction and trade sectors spike at similar times as the corresponding indicators of dispersion. There are spikes during the Democratic transition, the 1997-1998 recession, the two semi-recessions (in 2001 and 2003), and the Great Recession. In addition, all four indicators exhibit spikes during the European debt crisis in 2011, and again in 2014, at the start of the downswing phase at the end of the sample period. On the whole, however, the weighted sectoral indicators of dispersion seem to identify periods of uncertainty more accurately than the indicators of aggregate forecast error. This is also reflected in the higher correlations with real GDP growth, presented in Table 3.10 below.

Figure 3.18 illustrates the weighted sectoral indicators of idiosyncratic error uncertainty. These indicators do not always point to the same periods of heightened uncertainty than the ones highlighted above. The indicator of idiosyncratic error uncertainty in the manufacturing sector exhibits spikes in 1994, with the first Democratic election, and again in 1996, with the crisis in the foreign exchange market and the economic policy uncertainty before the adoption of the Growth, Employment and Redistribution (GEAR) framework (Koma, 2013). This indicator decreases during the Great Recession. The indicator in the construction sector exhibits a marked decrease during the 1997-1998 recession, which is following by spikes in 2000 and during the two semi-recessions. It is relatively flat for the rest of the period. The indicator for the trade sector is relatively volatile at the beginning of the period, and exhibits substantial decreases during all four recessionary periods. The indicator for the services sector is relatively high and volatile during the Great Recession, and exhibits a spike at the start of the final downswing phase in 2014.

In some cases, therefore, the individual indicators for each sector do not point to the same periods of heightened uncertainty. Table 3.10, below, reports that the indicators are weakly correlated only in

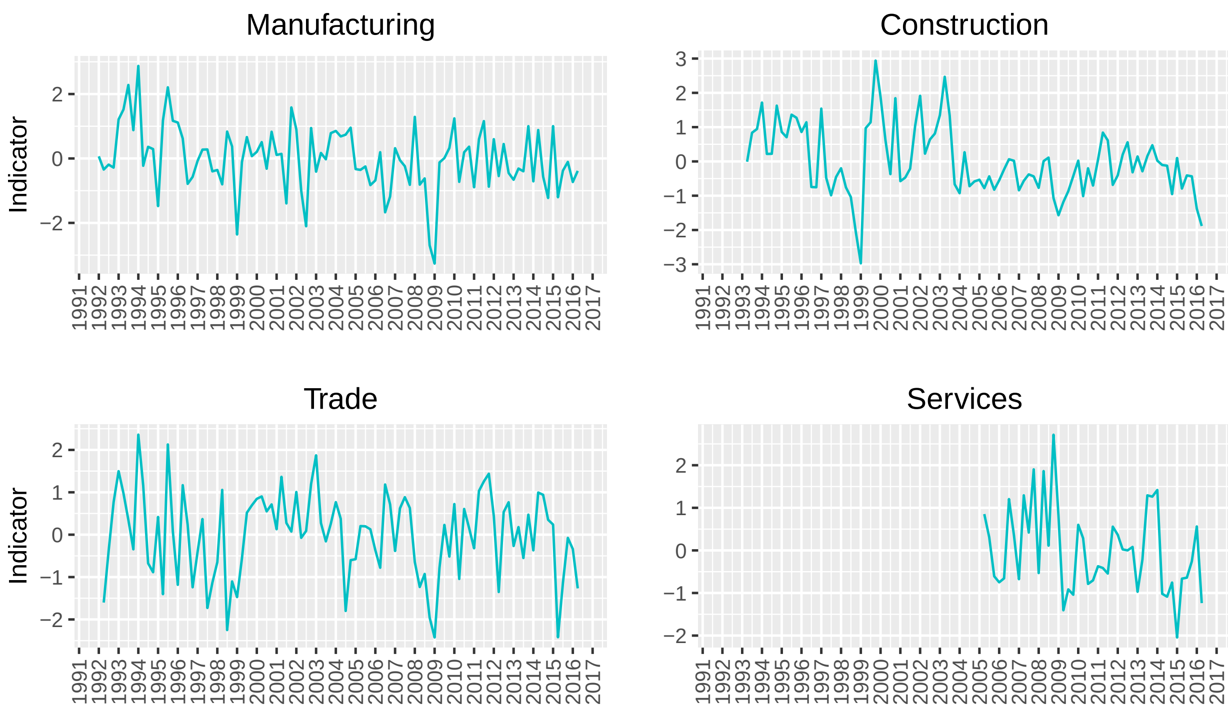

Figure 18: Weighted sectoral indicators of idiosyncratic forecast error uncertainty

a few cases. The lack of correlation is due to the 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 error and idiosyncratic error uncertainty indicators measure respectively the mean and standard deviation of firm forecast errors. Aggregate error uncertainty will increase if more firms make similar and larger errors, while idiosyncratic error uncertainty will decrease if more firms make similar errors. Consequently, the indicators do not generally point to the same periods of heightened uncertainty.

This feature is also present for the aggregate indicators. Figure 3.19 illustrates the three weighted uncertainty indicators at the aggregate level, with the recessionary periods shaded. As with the sectoral proxies, the indicators are relatively volatile, and are weakly correlated only in a few cases, as Table 3.9 below reports.

The dispersion indicator seems to follow an anti-cyclical pattern, with spikes during the recessionary periods. In particular, it points to periods of heightened uncertainty during the recessions of the early 1990s, the late 1990s, and the late 2000s. The aggregate error uncertainty indicator also seems to be broadly anti-cyclical. It exhibits large spikes in all four recessionary periods and during the two semi-recessions of the early 2000s. It also exhibits two large spikes in 2010 and 2011, during the period associated with the European debt crisis.

The idiosyncratic error 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 expected poorer general conditions with more certainty, as the recession took hold. Uncertainty about the future then increased around the trough, as expectations became more dispersed. The idiosyncratic error indicator also exhibits the two large

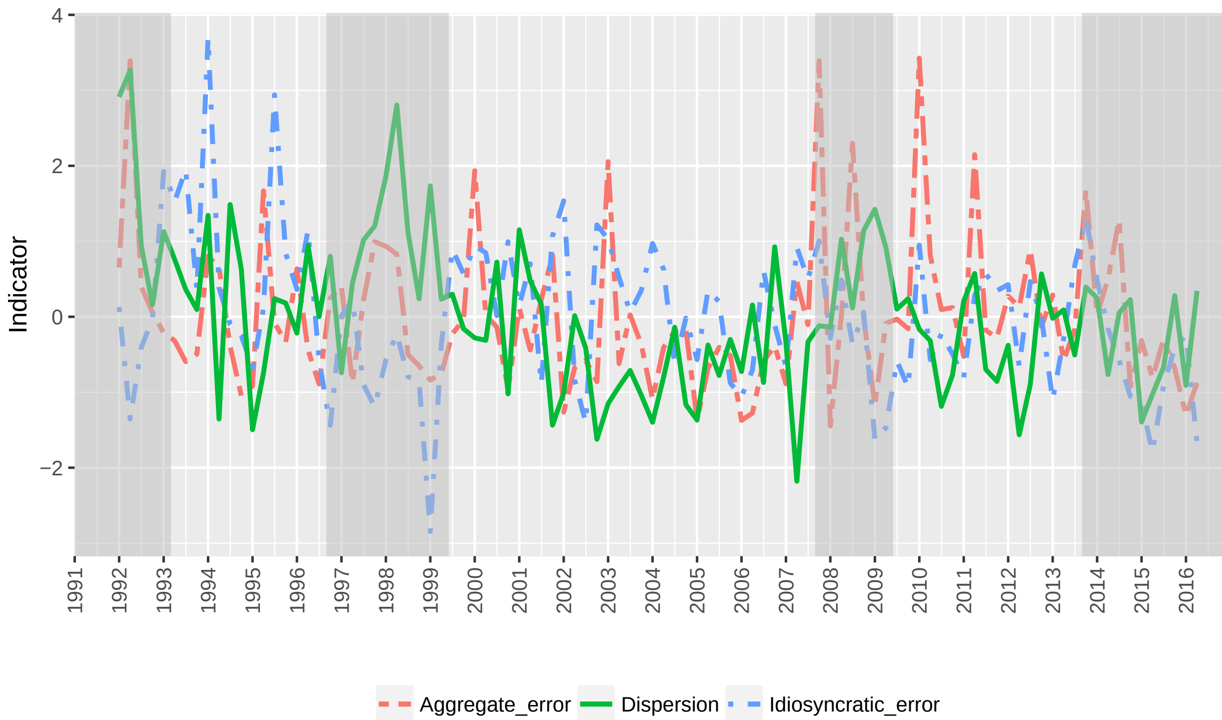

Figure 19: Weighted indicators of dispersion, aggregate error and idiosyncratic error uncertainty

spikes in 1994 and 1996, with the first Democratic election and the policy uncertainty before the adoption of the GEAR policy framework. More formal tests of validity are undertaken in the following section.

1.7.2 Validity Tests and Evaluation

This section provides a comparison of the survey-based uncertainty indicators and the two alternative indicators of uncertainty in South Africa, the EPU and the SAVI. The information from all of the indicators is combined to form an overall combined uncertainty indicator, and their correlations with real GDP growth are subsequently evaluated.

1.7.2.1 Correlations between uncertainty indicators and real GDP growth

Figure 3.20 illustrates the two alternative indicators, as well as the combined overall uncertainty indicator, which was calculated as the first principal component of the five standardised uncertainty indicators. Table 3.8 reports the factor loadings in calculating the combined uncertainty indicator. The dispersion measure and the EPU receive the highest weights in the calculation, while the idiosyncratic error indicator does not enter into the calculation. The results are similar when calculating the combined uncertainty measure as an equal weighted average, except that the idiosyncratic error indicator receives a higher weighting.

The combined indicator seems particularly plausible as a proxy for uncertainty, as a number of large spikes coincide with periods when uncertainty in South Africa was thought to be relatively

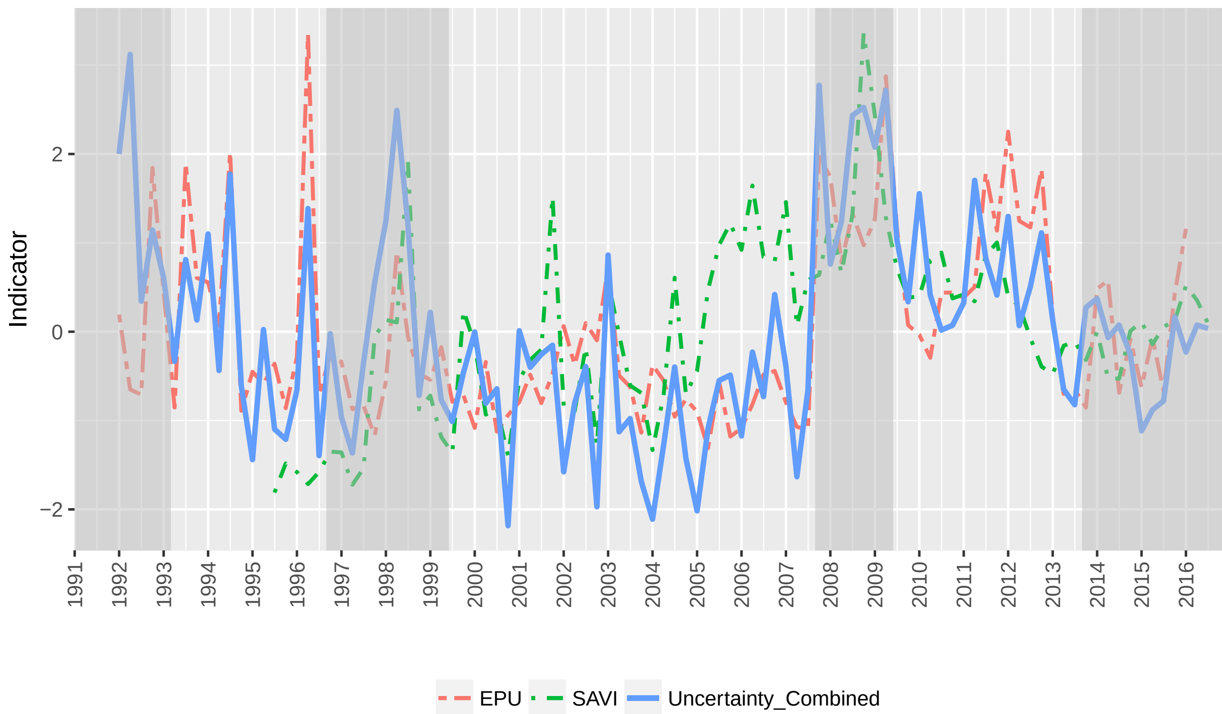

Figure 20: Indicators of economic policy, financial market, and combined uncertainty

Table 8: Factor loadings for the first principal component

Indicator	**Loadings**
Dispersion	0.55
Idiosyncratic error	0.00
Aggregate error	0.46
EPU	0.56
SAVI	0.41

high. For instance, uncertainty was relatively high during the Democratic transition up to 1994. There was quite a large spike, mainly in policy and idiosyncratic uncertainty, associated with the foreign currency crisis before the adoption of the GEAR strategy. Other spikes coincide with the East Asian and Russian crises, and the related recessionary period in 1997-1998; the semi-recession in 2003; the global financial crisis in 2008 and the subsequent recession; the European debt crisis in 2011; and the start of the downswing phase in 2014.

Table 3.9 reports the contemporaneous correlations between the indicators and real GDP growth. The dispersion, EPU and combined 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 idiosyncratic error uncertainty indicator does not exhibit the negative correlation with real GDP growth found in Bachmann, Elstner and Sims (2013).[9]

[9]It is possible that there is a structural explanation for the different relationship between idiosyncratic error uncertainty and real GDP growth. For instance, South African firms may react later to events such as recessions than US firms (i.e. they may be less forward-looking). Alternatively, it could be that something like growth effect is in operation in South Africa. There may also be problems with the survey data, either in terms of errors or

The individual indicators are only weakly correlated with one another in a few cases. This is not too surprising as they attempt to capture different types of uncertainty (Leduc and Liu, 2016). 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 focused specifically on policy uncertainty. This is the motivation for using a combined indicator, which captures different types of uncertainty from multiple sources.

The combined uncertainty indicator has a significant positive correlation with all of the indicators, except for idiosyncratic error uncertainty, which reflects the factor loadings used in deriving the first principal component. The dispersion indicator in particular, which in some ways in the simplest measure of uncertainty presented in this chapter, appears to drive the relationship between the combined index and GDP growth. It is therefore the most important measure of uncertainty presented in this chapter.

Table 9: Correlations between the uncertainty indicators

	Dispersion	Idiosyncratic_error	Aggregate_error	EPU	SAVI	Combined
Idiosyncratic_error	-0.15					
Aggregate_error	0.20*	0.18*				
EPU	0.14	0.08	0.09			
SAVI	0.06	-0.24**	0.07	0.28**		
Combined	0.64***	-0.10	0.54***	0.65***	0.56***	
RGDP_Growth	-0.44***	0.17*	-0.11	-0.30***	-0.11	-0.43***

Figure 3.21 illustrates the cross-correlograms for the uncertainty indicators and real GDP growth. All of the indicators, except for idiosyncratic error uncertainty, exhibit a significant negative correlation with real GDP growth, albeit at different horizons. All the indicators seem to lead changes in real GDP growth. The combined indicator exhibits the highest negative correlation with real GDP growth at a lag of two quarters.

Table 3.10 reports the contemporaneous correlations for the sectoral indicators and sectoral real GDP growth. The combined uncertainty indicator for each sector is the first principal component of the three survey-based measures. The indicators of dispersion and combined uncertainty for the manufacturing, construction, and trade sectors are significantly negatively, if weakly, correlated with contemporaneous real sectoral GDP growth.

Figure 3.22 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 error measures have a significant negative relationship with real GDP growth. The dispersion indicator again appears to drive the relationship between the combined index and GDP growth. The results for the construction and trade sectors are similar (not shown), while the indicators for the services sector (not shown) do not exhibit a negative relationship with real services GDP growth.

This section has presented three 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 of these imperfect measures may contribute to our

unrepresentativeness.

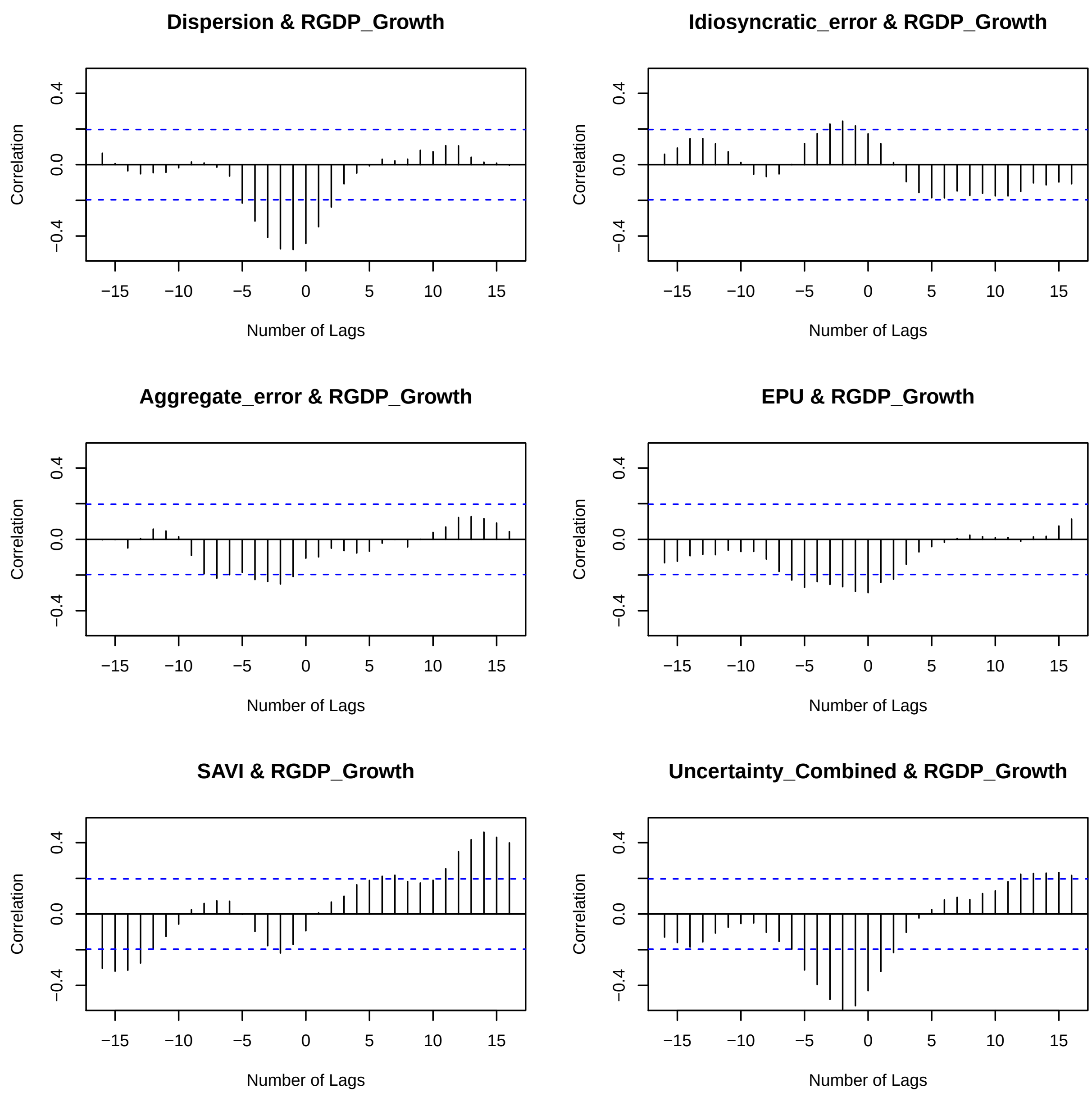

Figure 21: Cross-correlograms of uncertainty indicators and real GDP growth

Table 10: Correlations between the sectoral uncertainty indicators and real GDP growth

	Manufacturing				Construction			
	Dispersion	Aggregate	Idiosyncratic	Combined	Dispersion	Aggregate	Idiosyncratic	Combined
Aggregate	0.17*				0.39***			
Idiosyncratic	-0.28***	-0.02			-0.26**	0.17		
Combined	0.81***	0.46***	-0.69***		0.89***	0.73***	-0.27***	
RGDP	-0.30***	0.04	0.10	-0.22**	-0.18*	-0.17	-0.05	-0.19*
	Trade				Services			
	Dispersion	Aggregate	Idiosyncratic	Combined	Dispersion	Aggregate	Idiosyncratic	Combined
Aggregate	-0.01				-0.08			
Idiosyncratic	-0.22**	0.18*			-0.01	0.18		
Combined	0.58***	-0.56***	-0.81***		0.35**	-0.77***	-0.70***	
RGDP	-0.28***	-0.09	0.23**	-0.23**	-0.05	-0.19	0.29*	-0.06

understanding of uncertainty (Bachmann, Elstner and Sims, 2013). The five indicators were combined to form an overall combined uncertainty indicator, similar to those of Baker, Bloom and Davis (2015) and Redl (2015), to reflect the different sources of uncertainty from the different proxies. This combined indicator appears to be a plausible indicator of uncertainty in South Africa, reflecting key economic events. The composite dispersion and combined uncertainty indicators, in particular, improve on the existing uncertainty indicators in that they exhibit a larger negative correlation with real GDP growth.

1.8 The Relationship between Business Sentiment and Real Economic Activity

This section further examines the relationship between business sentiment and real economic activity in South Africa. This demonstrates the usefulness of the aggregation methods and the estimated indicators, and provides an additional validity test of the indicators. The hypothesis is tested that there is significant comovement between the sentiment indicators and real GDP growth. 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 investigate the dynamic effects of confidence and uncertainty shocks on the economy. A three-variable VAR and an extended VAR are then estimated to examine whether the results hold after the inclusion of additional variables.

1.8.1 Granger Causality Tests

Granger causality tests are often performed when investigating the comovement between 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 of future values of Y. If the hypothesis that a sentiment indicator does not Granger-cause an economic variable is rejected, it implies that past values of sentiment provide significant information for the economic variable, in addition to its own history.

Table 3.11 reports the results for Granger causality tests for the confidence indicators and real GDP growth. The results suggest that the lagged values of all four confidence indicators significantly predict real GDP growth, with no evidence of Granger-causality in the reverse direction. In other words, the results suggest that all the confidence indicators contain relevant information for the

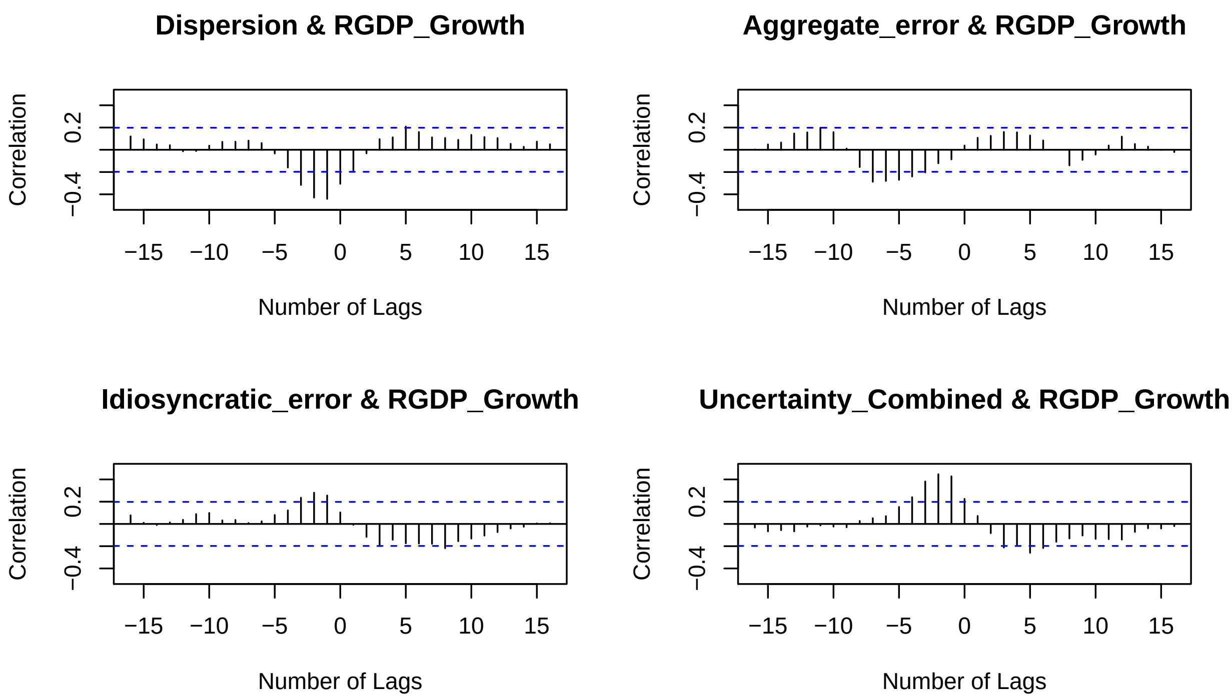

Figure 22: Cross-correlograms of manufacturing uncertainty indicators and real manufacturing GDP growth

prediction of output growth. This implies that the measures all exhibit a leading relationship with real GDP growth.

Table 3.12 reports the results of the Granger causality tests for the sectoral confidence indicators and their corresponding real sectoral GDP growth rates. The results are similar to those for the aggregate indicators, except for the trade sector, where lagged values of real GDP growth significantly predict all three survey-based confidence indicators. This implies that the confidence indicators for the trade sector are lagging indicators of real GDP growth in that sector.

Table 3.13 reports the results of Granger causality tests for the uncertainty indicators and real GDP growth. The results suggest that the lagged values of three of the uncertainty indicators significantly predict real GDP growth, with no evidence of Granger-causality in the reverse direction. In other words, the results suggest that the dispersion, aggregate error, and combined uncertainty indicators

Table 11: Granger causality tests: confidence

Granger causality H0:	**statistic**	**p-value**
Confidence (Current) does not Granger-cause RGDP Growth	2.70*	0.07
RGDP Growth does not Granger-cause Confidence (Current)	1.41	0.25
Confidence (Expected) does not Granger-cause RGDP Growth	3.44**	0.03
RGDP Growth does not Granger-cause Confidence (Expected)	0.58	0.56
BER BCI does not Granger-cause RGDP Growth	4.14**	0.02
RGDP Growth does not Granger-cause BER BCI	1.69	0.19
SACCI Growth does not Granger-cause RGDP Growth	3.23**	0.04
RGDP Growth does not Granger-cause SACCI Growth	0.03	0.97

Table 12: Granger causality test statistics: sectoral confidence

Granger causality H0:	**Manufacturing**	**Construction**	**Trade**	**Services**
Confidence (Current) does not Granger-cause RGDP Growth	4.85***	9.88***	1.04	3.10*
RGDP Growth does not Granger-cause Confidence (Current)	3.23**	1.37	3.86**	0.42
Confidence (Expected) does not Granger-cause RGDP Growth	8.10***	11.19***	1.40	5.90***
RGDP Growth does not Granger-cause Confidence (Expected)	2.45*	0.00	6.01***	0.07
BER BCI does not Granger-cause RGDP Growth	3.79**	5.63**	0.60	
RGDP Growth does not Granger-cause BER BCI	3.01*	0.03	2.84*	

Table 13: Granger causality tests: uncertainty

Granger causality H0:	**statistic**	**p-value**
Dispersion does not Granger-cause RGDP Growth	3.57**	0.03
RGDP Growth does not Granger-cause Dispersion	1.25	0.29
Aggregate error does not Granger-cause RGDP Growth	7.28***	0.00
RGDP Growth does not Granger-cause Aggregate error	0.13	0.88
Idiosyncratic error does not Granger-cause RGDP Growth	1.20	0.30
RGDP Growth does not Granger-cause Idiosyncratic error	0.98	0.38
EPU does not Granger-cause RGDP_Growth	0.93	0.43
RGDP Growth does not Granger-cause EPU	1.93	0.13
SAVI does not Granger-cause RGDP Growth	1.26	0.29
RGDP Growth does not Granger-cause SAVI	1.01	0.36
Uncertainty (Combined) does not Granger-cause RGDP Growth	5.85***	0.00
RGDP Growth does not Granger-cause Uncertainty (Combined)	0.06	0.94

contain relevant information for the prediction of output growth. This implies that these measures exhibit a leading relationship with real GDP growth.

The results for the sectoral indices, reported in Table 3.14, are not consistent across the sectors. There is some evidence of Granger-causality for a few of the indicators for the manufacturing sector. The tests are not significant at conventional levels in the trade sector, and in the construction sector only the combined uncertainty indicator significantly Granger-causes real trade GDP growth. In the services sector dispersion indicator seems to lag real GDP growth.

1.8.2 VAR Analysis

This section provides evidence on the dynamic effects of sentiment shocks on real economic activity. As many economic variables move together over time, without an obvious causal direction, it can be challenging to identify the directions of relationships. In the literature, timing has often been relied on for identification. This section follows the literature (e.g. Taylor and McNabb (2007); Barsky and

Table 14: Granger causality test statistics: sectoral uncertainty

Granger causality H0:	**Manufacturing**	**Construction**	**Trade**	**Services**
Dispersion does not Granger-cause RGDP Growth	7.50***	2.69	0.34	0.09
RGDP Growth does not Granger-cause Dispersion	1.76	0.01	0.46	4.54**
Aggregate error does not Granger-cause RGDP Growth	1.52	1.13	2.10	0.44
RGDP Growth does not Granger-cause Aggregate error	1.09	0.28	0.12	0.90
Idiosyncratic error does not Granger-cause RGDP Growth	3.18**	0.42	1.48	1.61
RGDP Growth does not Granger-cause Idiosyncratic error	1.14	0.57	0.73	2.33
Uncertainty (Combined) does not Granger-cause RGDP Growth	9.61***	2.99*	1.60	0.76
RGDP Growth does not Granger-cause Uncertainty (Combined)	1.35	0.02	0.87	1.59

Sims (2012); Bachmann, Elstner and Sims (2013)) in using standard recursive VARs to trace out the dynamic responses of economic activity to surprise shocks in sentiment. The aim is to investigate whether the indicators have a significant dynamic relationship with real output, whether they contain predictive content for output growth, and whether shocks to sentiment generate responses that are in line with the theory and the findings in the literature.

The relationships were investigated for the aggregate variables, as well as separately for each sector, using bivariate recursive VARs featuring a measure of sentiment 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 sentiment, and ϵ is the residual of each equation.

A range of VARs were estimated for the quarterly data running from 1992Q1 to 2016Q3. The indicators enter in levels, while the real GDP series enter as annual quarter-on-quarter growth rates, which corresponds with the survey reference period. Unit root tests, reported in the Appendix, indicate that virtually all of the aggregate and sectoral indicators, and the corresponding real GDP growth rates are stationary. The exception is confidence on current conditions in the services sector, which may be due to the relatively short 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, homoskedasticity and normality) are satisfied. In the majority of cases, the information criteria point to two 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 sentiment are allowed to have a contemporaneous impact on output, but shocks to output have no contemporaneous impact on sentiment ($\beta_{21} = 0$). In other words, innovations to the confidence indicators influence economic output on impact, but not vice versa. This is the identification strategy and ordering used in the literature (e.g. Leduc and Sill (2013), Bachmann, Elstner and Sims (2013), Girardi and Reuter (2017), Baker, Bloom and Davis (2016), and Redl (2015)). It can be motivated by the timing of the surveys before the release of most macroeconomic data (Leduc and Liu, 2016). 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.

1.8.2.1 Confidence

Impulse response functions (IRFs) can be generated to illustrate the dynamic impact of a shock to sentiment on the system. The shock is an innovation of one standard deviation to the residual in the equation. Figure 3.23 illustrates the IRFs of a bivariate VAR for the confidence indicator on current conditions and real GDP growth. The left panel plots the responses of real GDP growth to an orthogonal shock in the indicator, with 95% bootstrap confidence intervals. Following an increase in confidence of one standard deviation, real GDP growth increases by around 0.3% on impact, with a peak at two quarters. The impact on the growth rate is transitory, dying out after approximately seven quarters. This is equivalent to a permanent increase in the level of output, which corresponds

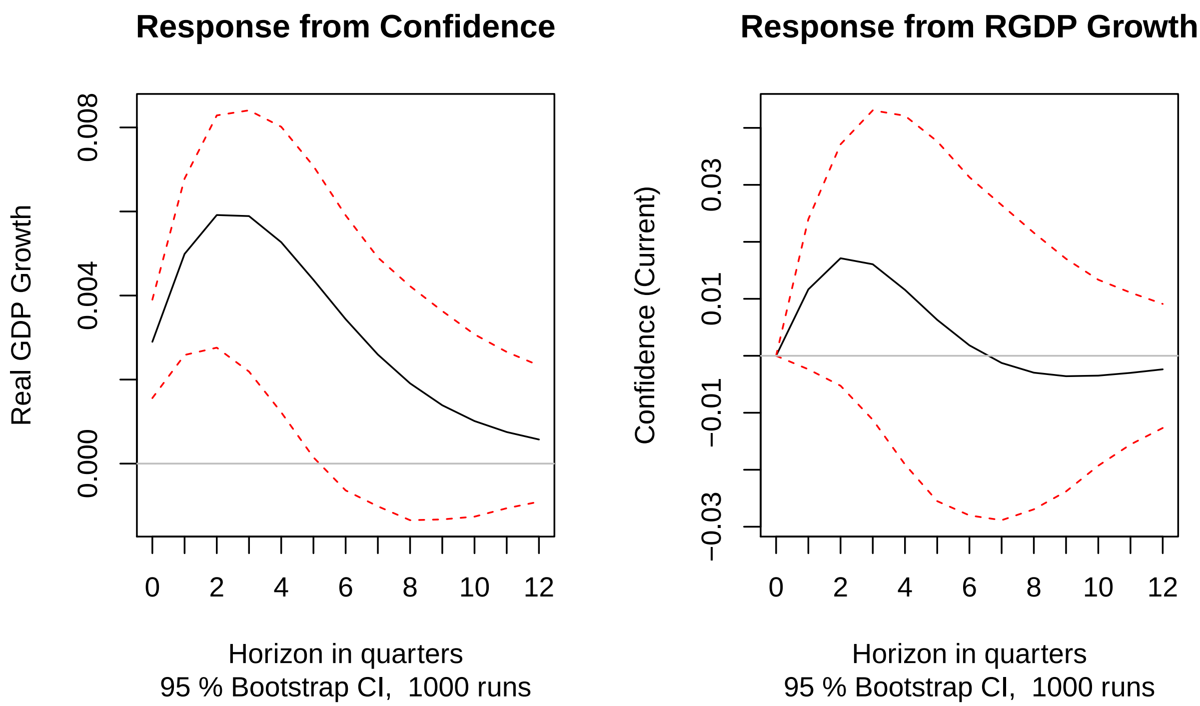

Figure 23: IRFs of confidence (current conditions) and real GDP growth

to the findings in the literature (e.g. Barsky and Sims (2012)). The right panel plots the response of confidence to an orthogonal shock in real GDP growth. Following an increase in real GDP growth, there is an insignificant increase in confidence of around 2% after two quarters. The results are similar for alternative orderings. As reported in the Appendix, the results are remarkably similar for the confidence indicator on expected conditions and the BER BCI, whereas the SACCI growth rate exhibits a smaller significant relationship with real activity after two quarters.

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 Reuter, 2017). The forecast error variance decomposition (FEVD) shows the proportion of the movements in a sequence due to its own shocks and shocks to the other variable. Figure 3.24 illustrates the FEVDs for the current conditions confidence indicator and real GDP growth. Up to around half (46%) of the movements in real GDP growth are explained by the confidence indicator over the longer term, while real GDP explains up to 2% of the variance in the confidence indicator.

The results for the sectoral indicators are very similar to the aggregate results. Figure 3.25 illustrates the IRFs of a bivariate VAR for the current conditions confidence indicator in the manufacturing sector and real GDP growth in the manufacturing sector. Following an increase in confidence, real GDP growth increases on impact, with a peak at two quarters. The impact on the growth rate dies out after approximately four quarters. Following an increase in real GDP growth, there is a significant increase in confidence in the following quarter. The results are similar for alternative orderings. The results for the other sectoral indicators (not shown) are very similar to those for the

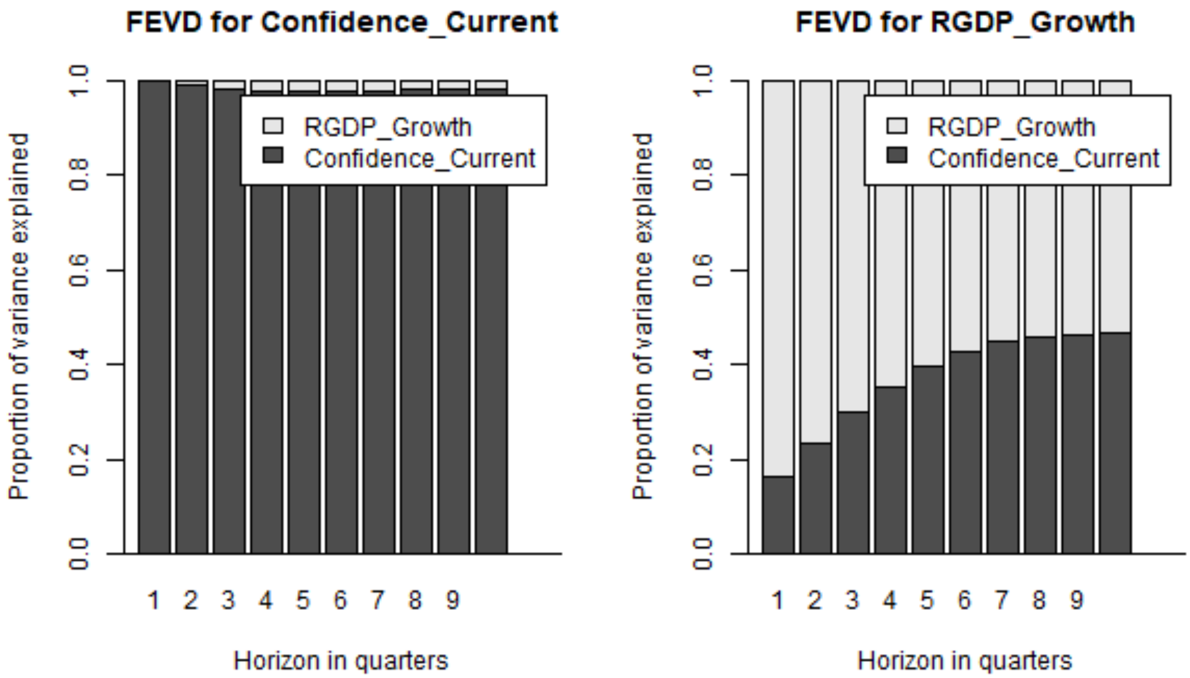

Figure 24: FEVDs of confidence (current conditions) and real GDP growth

manufacturing sector, with the exception that in the construction sector, the impact of a shock to confidence on GDP growth does not die out within the forecast horizon of 12 quarters.

Figure 3.26 illustrates the FEVDs for the current conditions confidence indicator and real GDP growth in the manufacturing sector. Up to more than a third (37%) of the movements in real GDP growth are explained by confidence over the longer term, while real GDP explains up to 5% of the variance in confidence. Overall, the results suggest that shocks to the confidence indicators account for between 20% and 60% of the forecast error variance of the real GDP growth rate, depending on the level of aggregation and the indicator.

1.8.2.2 Uncertainty

Figure 3.27 illustrates the IRFs of a bivariate VAR with the dispersion indicator 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 of one standard deviation to dispersion is followed by a significant decrease in real GDP growth in the following quarter. The right panel plots the response of dispersion to an orthogonal shock in real GDP growth. Following a shock to real GDP growth, there is an insignificant response in the dispersion indicator. The IRFs for the aggregate error, EPU, and SAVI indicators of uncertainty are very similar. Shocks to these indicators are associated with a moderately significant decreases in real GDP growth, while shocks to real GDP growth do not lead to a significant changes in the uncertainty indicators. The IRFs for the idiosyncratic error uncertainty indicator are not significant. The results are similar for alternative orderings.

Figure 3.28 illustrates the IRFs of a bivariate VAR with the combined uncertainty indicator and real

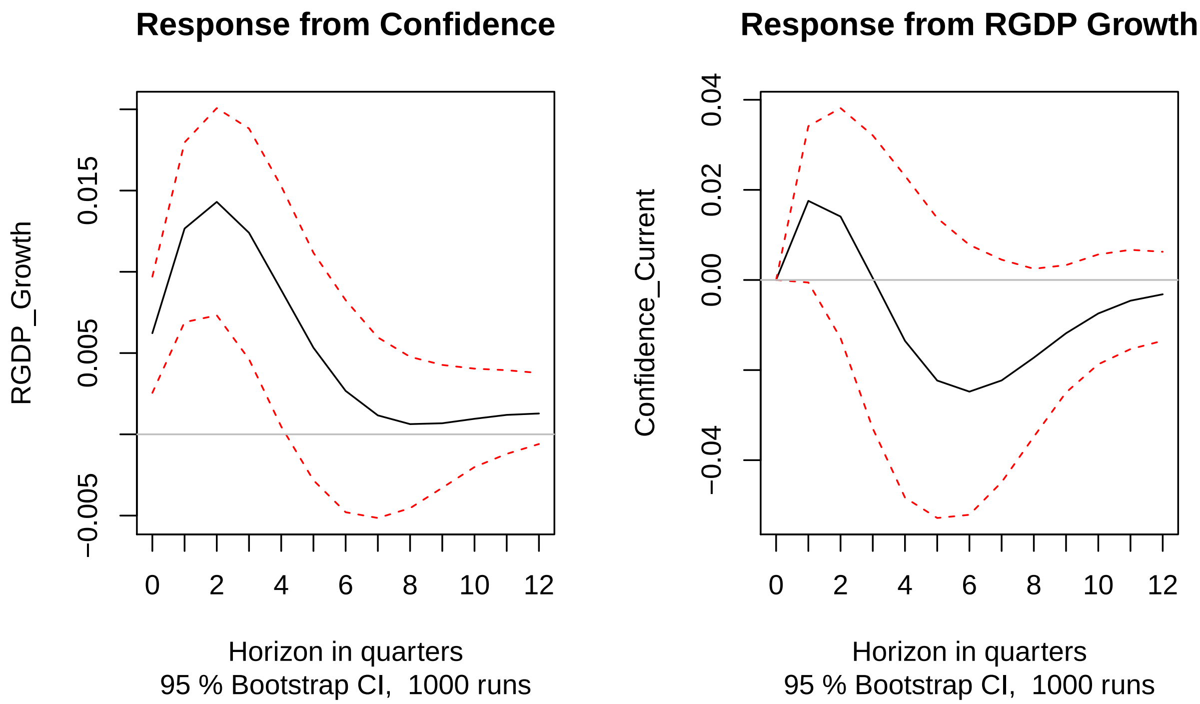

Figure 25: IRFs of confidence (current) and real GDP growth in the manufacturing sector

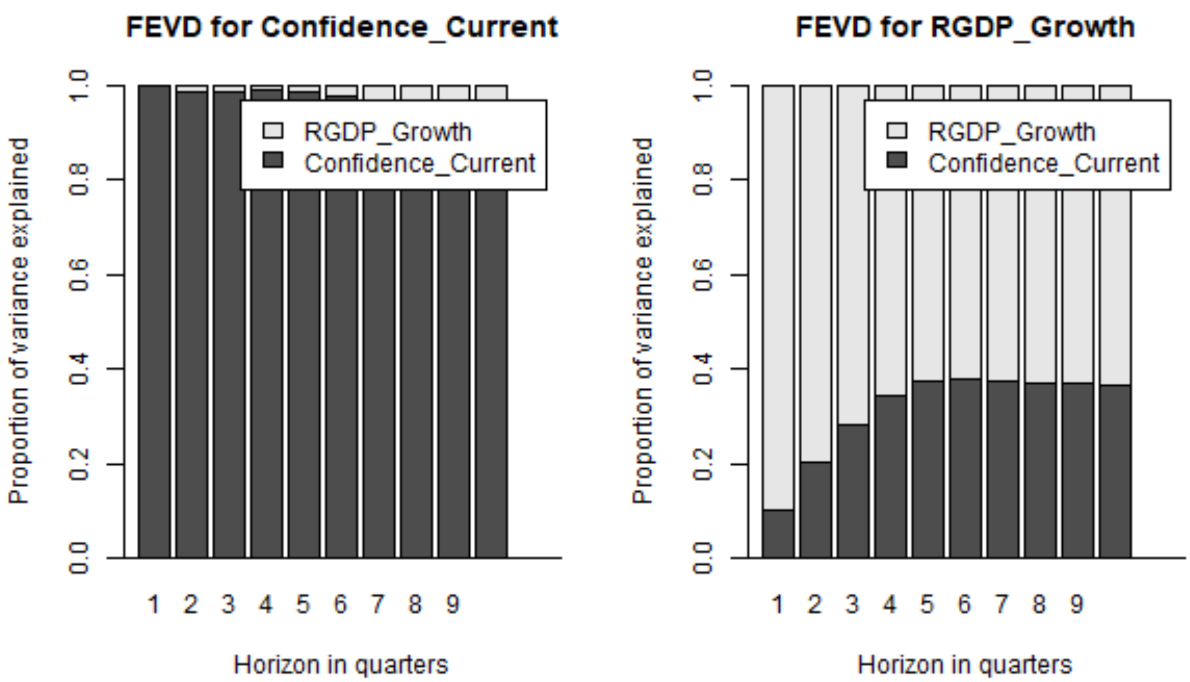

Figure 26: FEVDs of confidence (current) and real GDP growth in the manufacturing sector

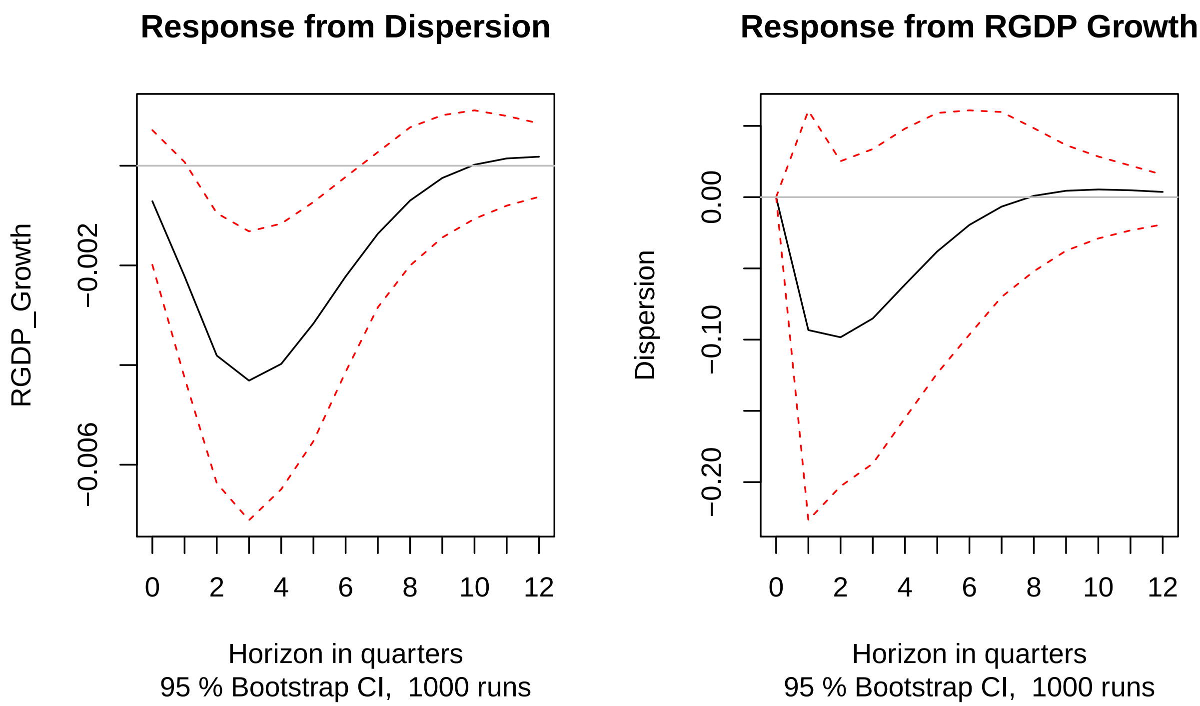

Figure 27: IRFs of dispersion and real GDP growth

GDP growth. A shock to uncertainty is followed by a significant decrease in real GDP growth, with a peak at three quarters. The impact is larger and more significant than for any of the component uncertainty indicators separately. The impact on the growth rate is also transitory, dying out after approximately seven quarters. This result corresponds to the findings in much 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 3.29 illustrates the FEVDs for the combined uncertainty indicator and real GDP growth. Over 30% of the movements in real GDP growth are explained by the uncertainty indicator over the longer term, while real GDP explains about 1% of the variance in uncertainty. This is in line with findings in the literature (e.g. Bachmann, Elstner and Sims (2013)).

Figure 3.30 illustrates the IRFs of a bivariate VAR for the combined manufacturing uncertainty indicator and real GDP growth in the manufacturing sector. A shock to uncertainty is followed by a significant decrease in real GDP growth, with a peak at two quarters. There is even some evidence of a subsequent rebound predicted by the 'wait-and-see' effect demonstrated in Bloom (2009). The FEVDs illustrated in Figure 3.31 show that around 30% of the movements in real manufacturing GDP growth are explained by uncertainty over the longer term.

There is no consistent negative relationship for any single indicator and real GDP growth in the other three sectors (not shown). In the construction sector, the dispersion and combined uncertainty indicators have a significant negative impact on real GDP growth. In the trade sector, only the dispersion indicator has a significant negative impact, while in the services sector only the idiosyncratic error indicator has a significant impact on real GDP growth.

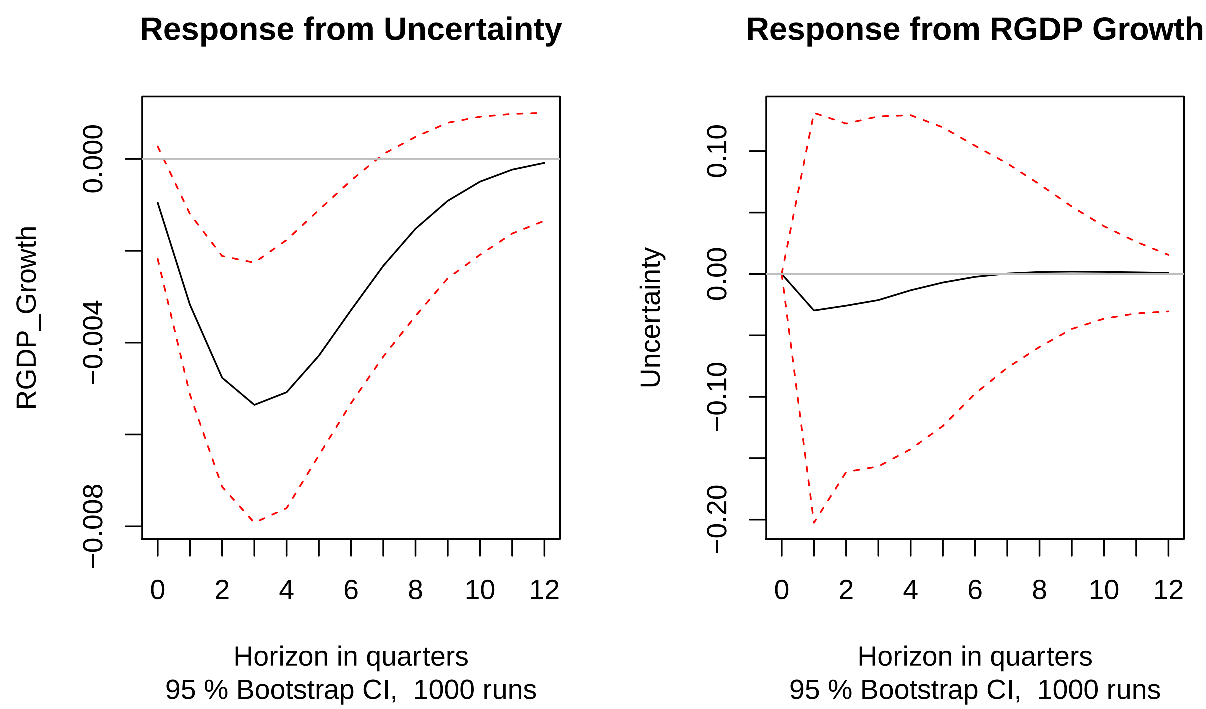

Figure 28: IRFs of uncertainty (combined) and real GDP growth

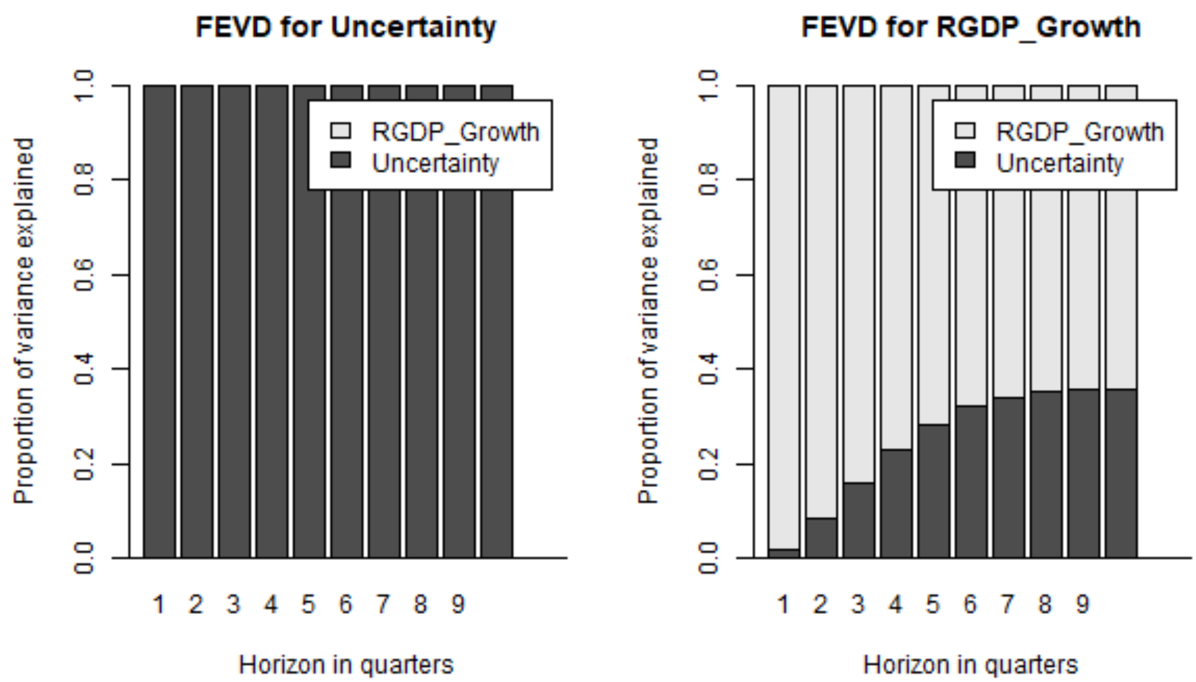

Figure 29: FEVDs of uncertainty (combined) and real GDP growth

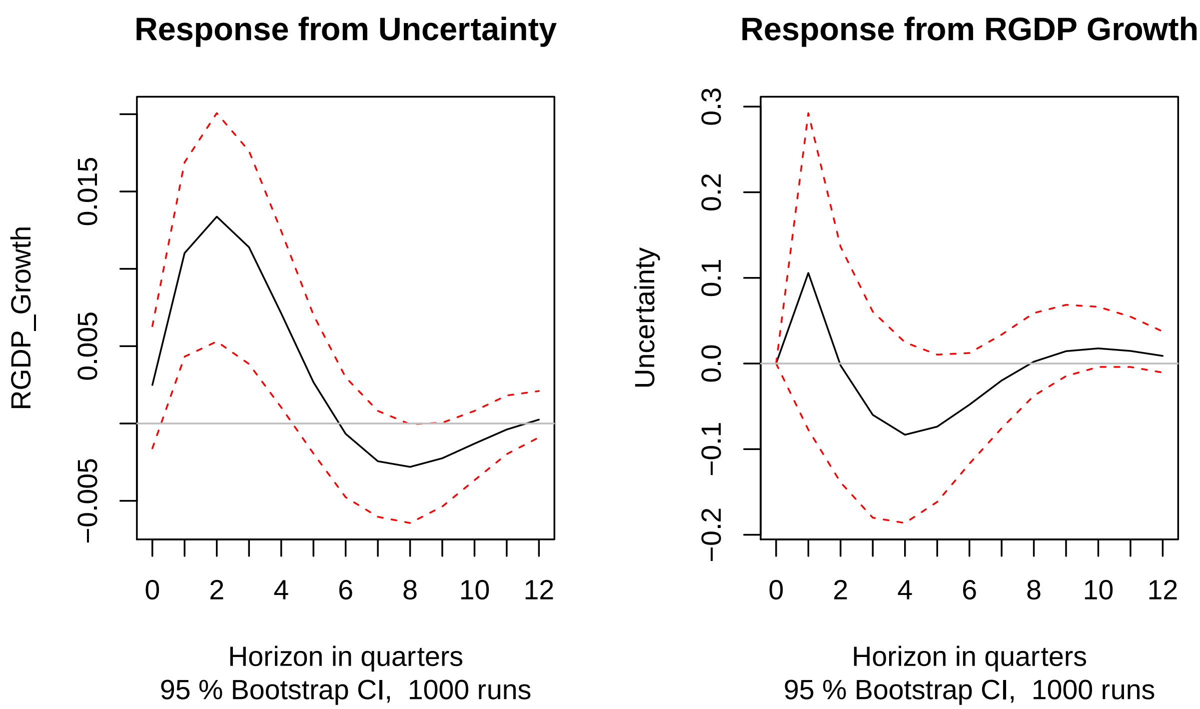

Figure 30: IRFs of uncertainty (combined) and real GDP growth in the manufacturing sector

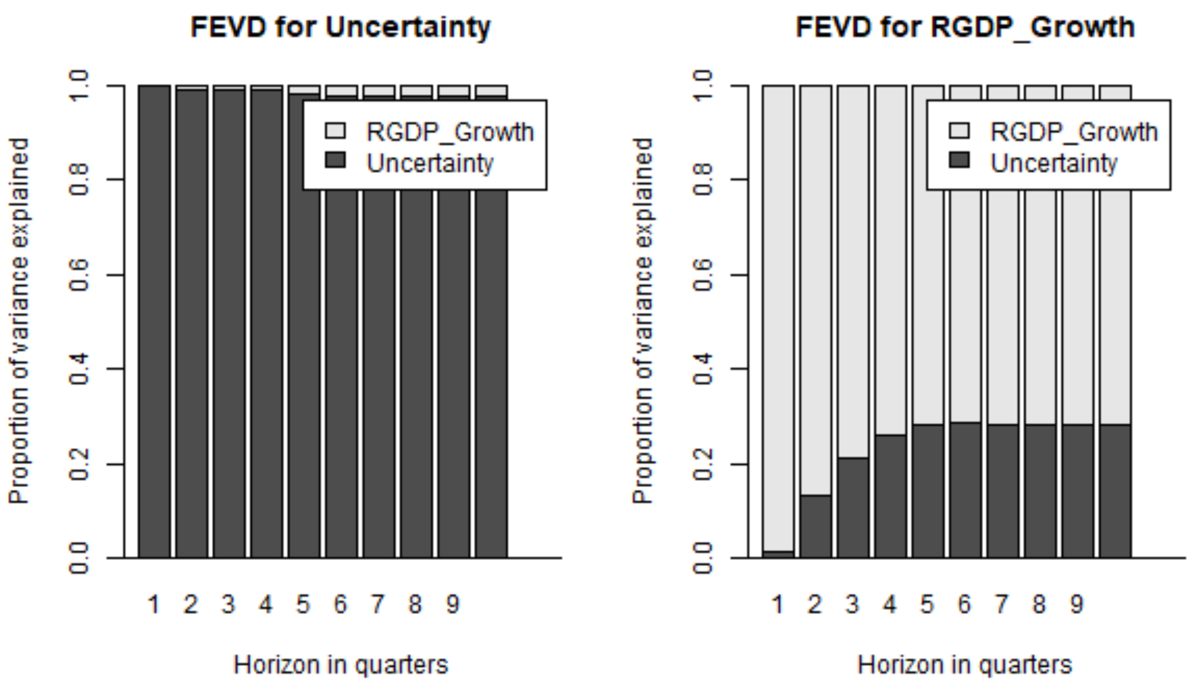

Figure 31: FEVDs of uncertainty (combined) and real GDP growth in the manufacturing sector

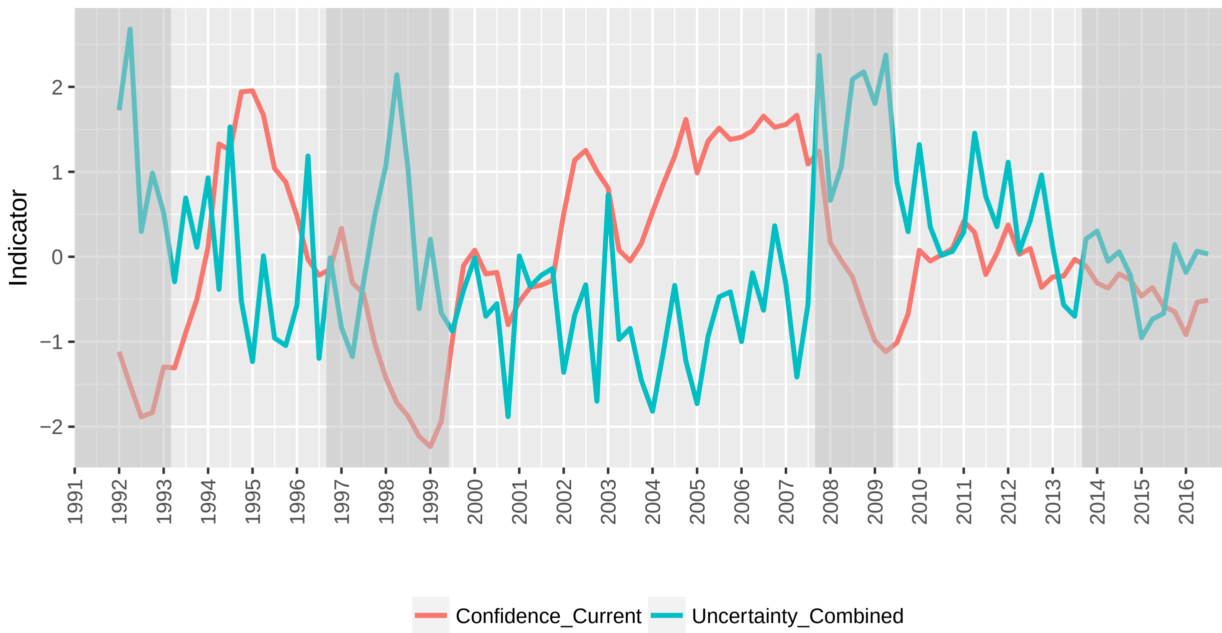

Figure 32: Confidence (current) and uncertainty (combined)

1.8.2.3 Expanded VAR

Though instructive, the results from a bivariate system are prone to misspecification (Girardi and Reuter, 2017). 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 (e.g. Girardi and Reuter (2017), Leduc and Liu (2016), Baker, Bloom and Davis (2016) 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 of an uncertain future (Baker, Bloom and Davis, 2016).

Figure 3.32 illustrates the current conditions measure of confidence and the combined uncertainty indicator with recessionary periods shaded. The two sentiment indicators do not appear to be mirror images of each other, with a correlation of -0.36. Although confidence is pro-cyclical and uncertainty is mostly anti-cyclical, they appear to capture different phenomena.

Figure 3.33 illustrates the IRFs of a three-variable VAR including confidence on current conditions, combined uncertainty and real GDP growth. Following Girardi and Reuter (2017), confidence was ordered first under a recursive identification scheme. The results are very similar to the IRFs for the bivariate VARs reported earlier. A positive shock to confidence is followed by a significant increase in real GDP growth, while a positive shock to uncertainty is followed by a significant decrease in real GDP growth. Figure 3.34 illustrates the FEVDs for this three-variable VAR. Up to around 30% of the variance in real GDP growth is explained by confidence over the longer term, while uncertainty explains around 25% of the variance.

A larger VAR system was also estimated to test the robustness of the relationships. The extended VAR includes the variables suggested by Redl (2015) for South Africa: confidence, uncertainty, the JSE All Share Index, the yield spread (i.e. the Government Bond Yield minus the three-month

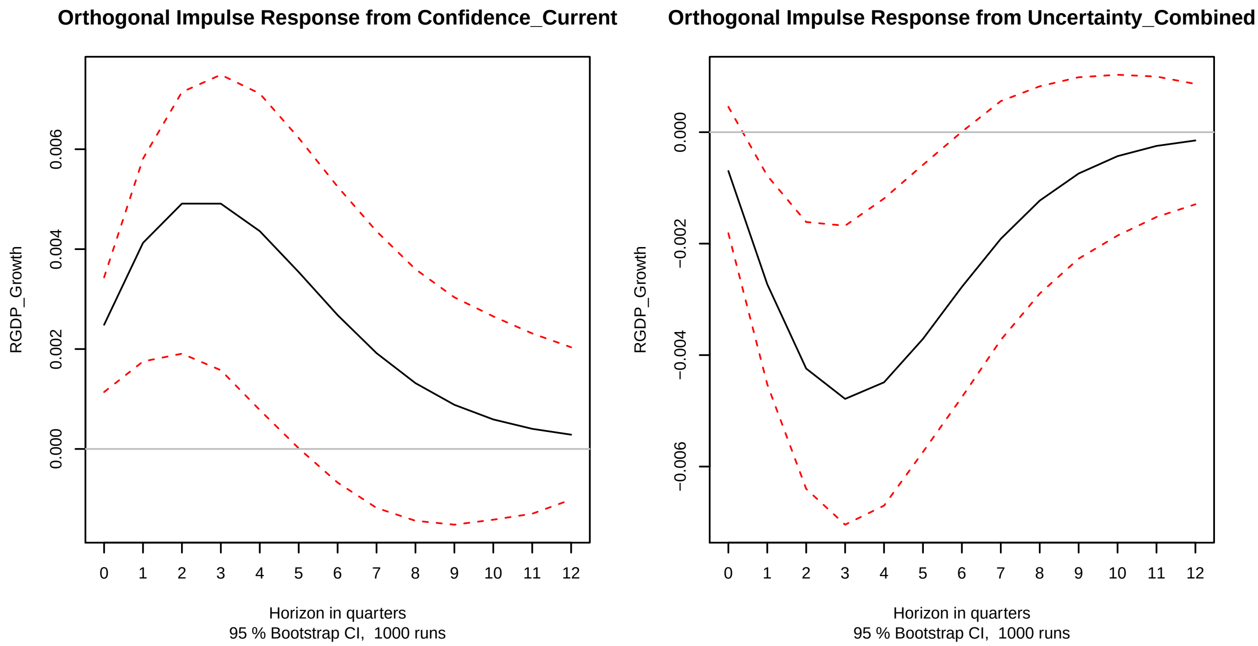

Figure 33: IRFs of real GDP growth to confidence and uncertainty in the three-variable VAR

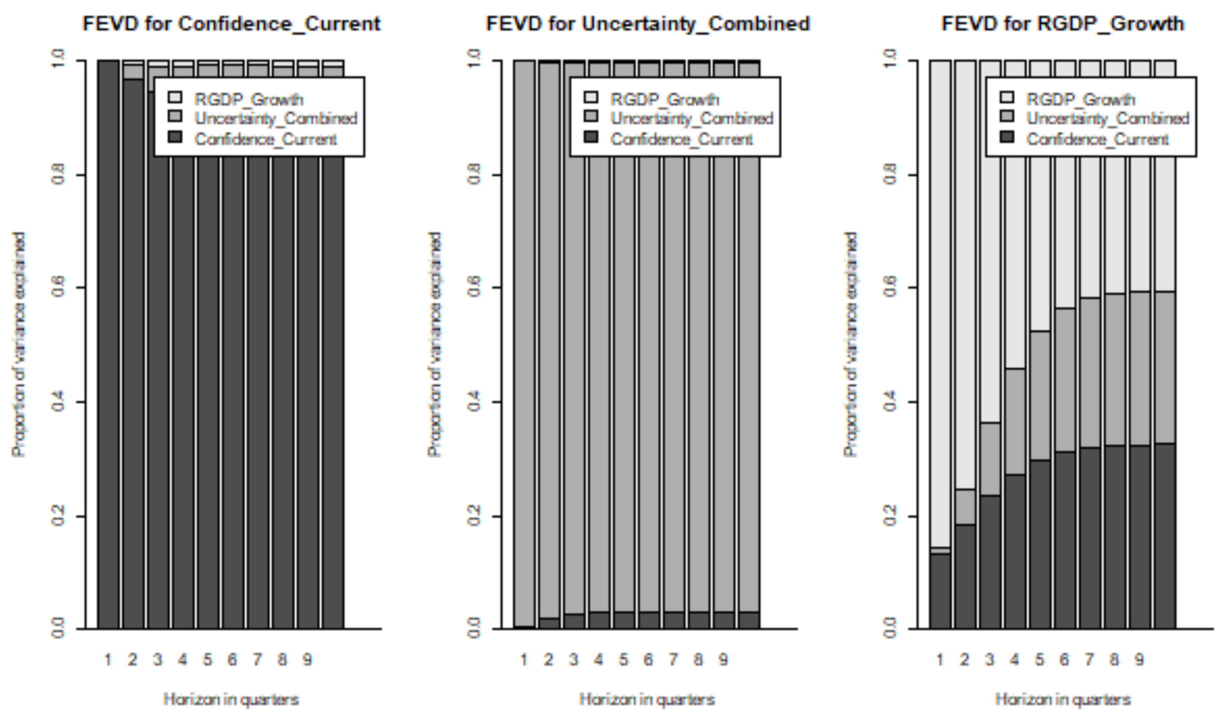

Figure 34: FEVDs of the three-variable VAR

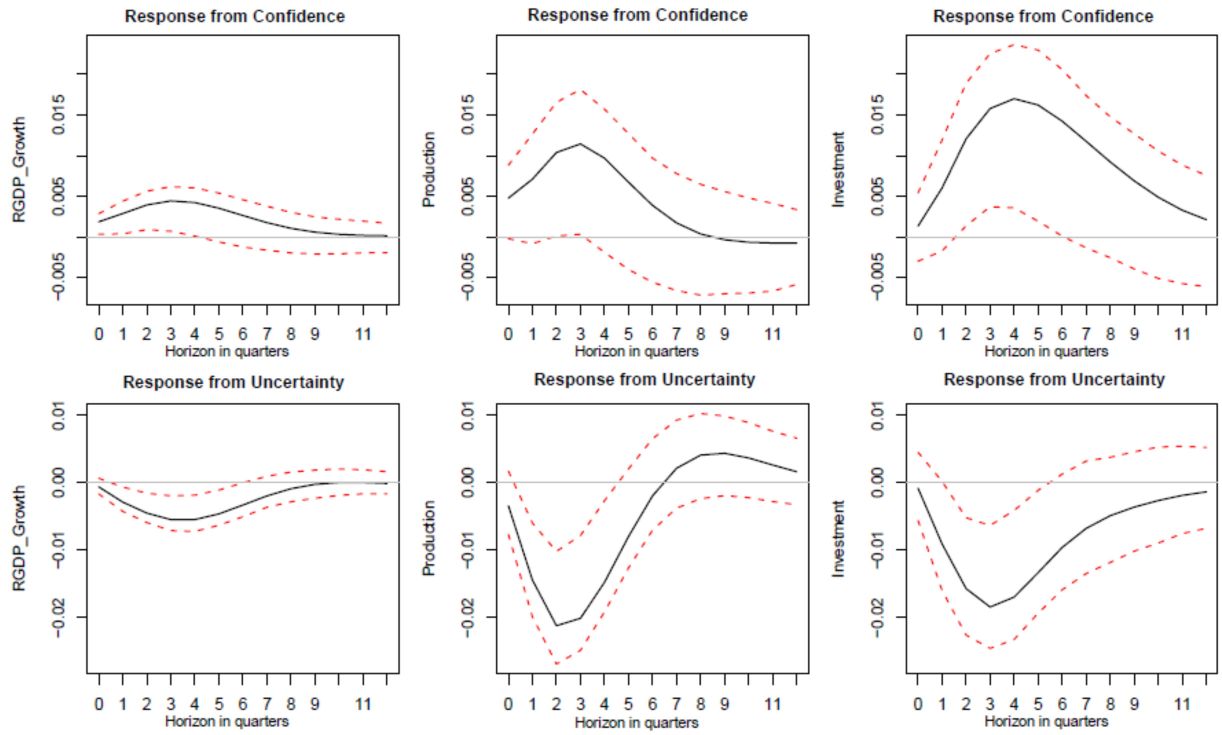

Figure 35: IRFs of real GDP, production and investment growth to confidence and uncertainty

T-Bill rate), GDP, industrial production, investment, and an employment index. These variables are typically included in the literature (e.g. Leduc and Sill (2013), Bachmann, Elstner and Sims (2013), and Baker, Bloom and Davis (2016)).

The variables were ordered with the sentiment variables first, the financial variables next and the real variables last. The financial variables were expected to move faster than the real variables (Redl, 2015). An alternative ordering of placing the sentiment indicators last provides qualitatively similar results. As was the case in the previous VARs, the variables enter as real annual quarter-on-quarter growth rates, except for the sentiment indices and the yield spread. The model was estimated with two lags, with the caveat that the information criteria indicate that more than the maximum number of lags are appropriate. The results with four lags are qualitatively similar.

The IRFs for the impact of confidence (current conditions) and uncertainty (combined) on the growth rate of real GDP, real production and real investment are illustrated in Figure 3.35. The top panels illustrate the responses of the real variables to a shock in confidence, and the bottom panels show the responses to a shock in uncertainty. The larger system seems to provide similar results to the findings in bivariate VARs. The response in real GDP growth are similar to those in the three-variable model. The impacts of the shocks are larger on real production and investment growth than on real GDP growth. This is what the wait-and-see theory would predict. The responses of employment (not illustrated) are very similar to those of real GDP growth. According to the FEVD (not shown), confidence explains around 35%, 25%, and 40% of the variance in real GDP growth, real production growth and real investment growth respectively, while uncertainty explains around 15%, 25% and 20% of the variance in the three real variables.

1.9 Conclusion

This chapter attempted three contributions to the literature. The first was to demonstrate aggregation methods to estimate sentiment indicators from the disparate qualitative responses of individual firms. The chapter used different combinations of the weighted cross-sectional first and second moments of the distribution of the qualitative survey responses to create composite indicators of confidence and uncertainty.

The weighted cross-sectional moments employed in this chapter would be useful in other applications with qualitative survey responses, such as consumer surveys, where there are challenges in capturing the full richness in the data. Consumer confidence measures are popular indicators and are often calculated using qualitative surveys. Examples include the European Commission's Consumer Confidence Indicator and the University of Michigan's Consumer Sentiment Index for the US (United Nations, 2015). The BER calculates consumer confidence for South Africa using their consumer tendency surveys. It would be possible to improve on the existing measures of consumer confidence using the techniques demonstrated in this chapter to identify an underlying pattern from the disparate views of individual agents. Moreover, it would be possible create new measures of consumer uncertainty, by calculating the scaled cross-sectional dispersion of responses (which does not require a panel), as long as there are forward-looking questions as well as questions on current conditions. The consumer sentiment indicators may also be combined with the business sentiment indicators to create general sentiment indicators, in the same way in which the European Commission creates its Economic Sentiment Index.

The second contribution was to produce new composite indicators of confidence and uncertainty for South Africa, which are reported in Table 3.19 in the Appendix below. The sectoral indicators are available on request. The new composite indicators outperformed the existing confidence indicators in terms of their correlation with real GDP growth and their concordance with the official SARB business cycle. The BER BCI is often used as a leading indicator of the business cycle, for example, by the SARB and Laubscher (2014). The new confidence indicators may therefore be useful as improved leading indicators of the business cycle. The composite dispersion and combined uncertainty indicators, in particular, exhibited larger negative correlations with real GDP growth than the existing uncertainty indicators.

The third contribution was to use these indicators to contribute to the literature on the relationship between sentiment and real economic activity in the South African setting. The results provide evidence of at least important comovement between the indicators of sentiment and real economic activity. Both sets of sentiment indicators contained significant predictive information for real economic activity, even after controlling for additional variables.

The indicators might be useful for forecasting and nowcasting exercises, especially given that they are available before official statistics are published. The GDP figures used in this chapter are the revised numbers, which are only produced after a significant delay. When the indicators are used for real-time forecasting, however, the issue of data revisions becomes a problem. Econometric forecasts are typically based on revised data but are evaluated against the first release data. However, as Van Walbeek (2006) noted for South Africa, the growth in GDP has been subject to significant upward revisions and bias, especially after 1994. Forecast estimation using the first release versions of the GDP figures would most likely produce markedly different estimates to those using the revised data. In such a case, a 'poor forecast' could in fact be a poor first release of the official data (Van Walbeek, 2006). Future research might evaluate the performance of the indicators in real time, as well as the impact of official data revisions.

The uncertainty indicators could be used to further investigate the importance of uncertainty shocks for business cycle fluctuations and credit cycles, and whether this relationship is non-linear or asymmetric. The forecasting ability of the indicators might be offset completely by other variables during ordinary times, while increasing notably in the presence of unusual events. For instance, shocks to sentiment might play an important role only during episodes of economic tension associated with large decreases in confidence and heightened uncertainty. It may also be used to inform other analyses, such as the influence of uncertainty on the responsiveness of exports to relative price changes, studied in Hlatshwayo and Saxegaard (2016).

The results imply that the current climate of heightened political uncertainty and weak consumer and business confidence are potential determinants of the lower growth that the South African economy is currently experiencing, as argued by the International Monetary Fund (2017). Future research could try to identify the potential causal impact of these changes in sentiment. Moreover, it may be informative to investigate the factors that drive the indicators of sentiment. The new sentiment indicators created in this chapter may facilitate these inquiries.

1.10 Appendix

1.10.1 Confidence Intervals for the Confidence Indicators

This section illustrates confidence intervals around the confidence indices. The intervals are calculated as two times the standard deviation of the weighted sample mean. Figure 3.36 illustrates 95% confidence intervals around confidence indicators on current and expected conditions. Figure 3.37 illustrates 95% confidence intervals around the sectoral confidence indicators on current conditions. The confidence intervals show that the distribution of the sample means are relatively narrow, because of the large number observation in each quarter. As a consequence, the changes in the indices seem to be 'real' changes rather than statistical idiosyncrasies. The confidence intervals for the scaled dispersion indicator (not reported) are similarly narrow and imply that the changes are real.

1.10.2 Stable Sample Indicators

In order to test whether the entry and exit or attrition rates of firms drive the results, a number of robustness exercises are carried out. In this section the indicators are calculated by including only firms that form part of smaller, more 'stable', samples, which are then compared to the full sample indicators.

1.10.2.1 The sample of firms that responded in consecutive periods (forecast error sample)

This section presents the confidence and uncertainty indicators based on firms that responded in consecutive quarters (i.e. the forecast error sample). Figure 3.38 and Figure 3.39 compare the full sample indicators to those based only on the more stable forecast error sample. Table 3.15 reports that the correlations between these indicators are high and significant. The table also reports the correlations between the smaller forecast error sample indicators and real GDP growth, which are

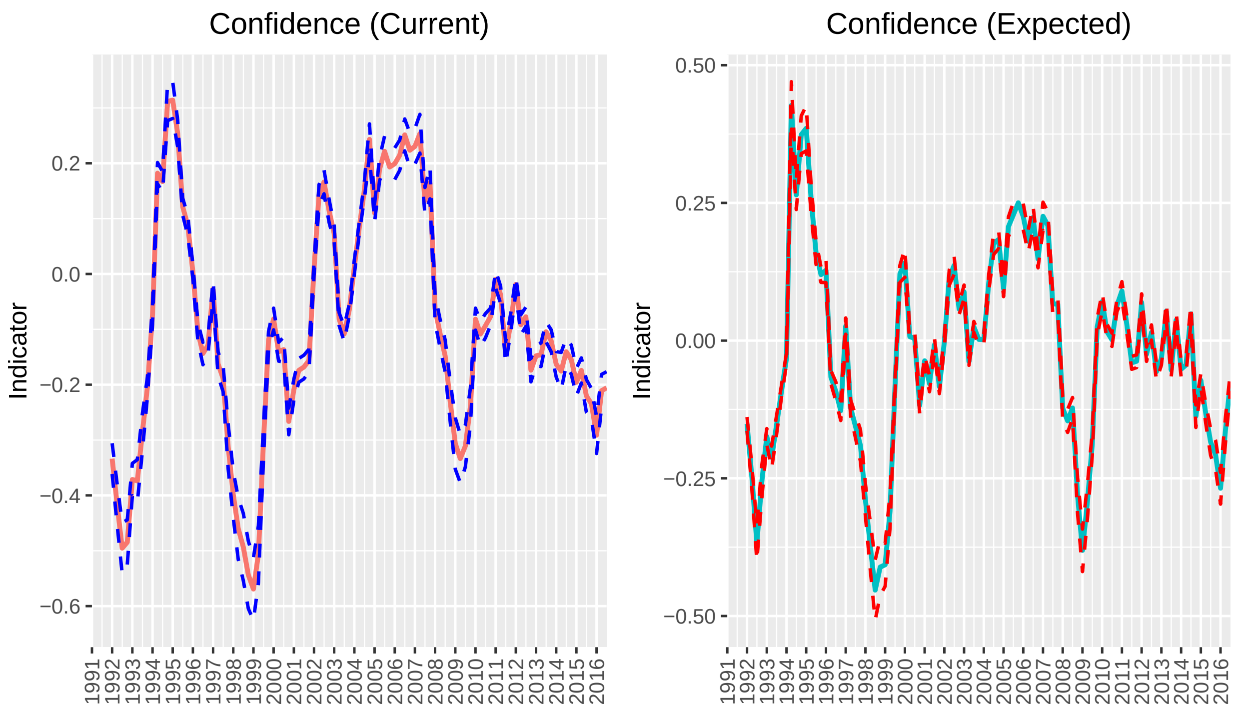

Figure 36: Confidence indicators with 95% confidence intervals

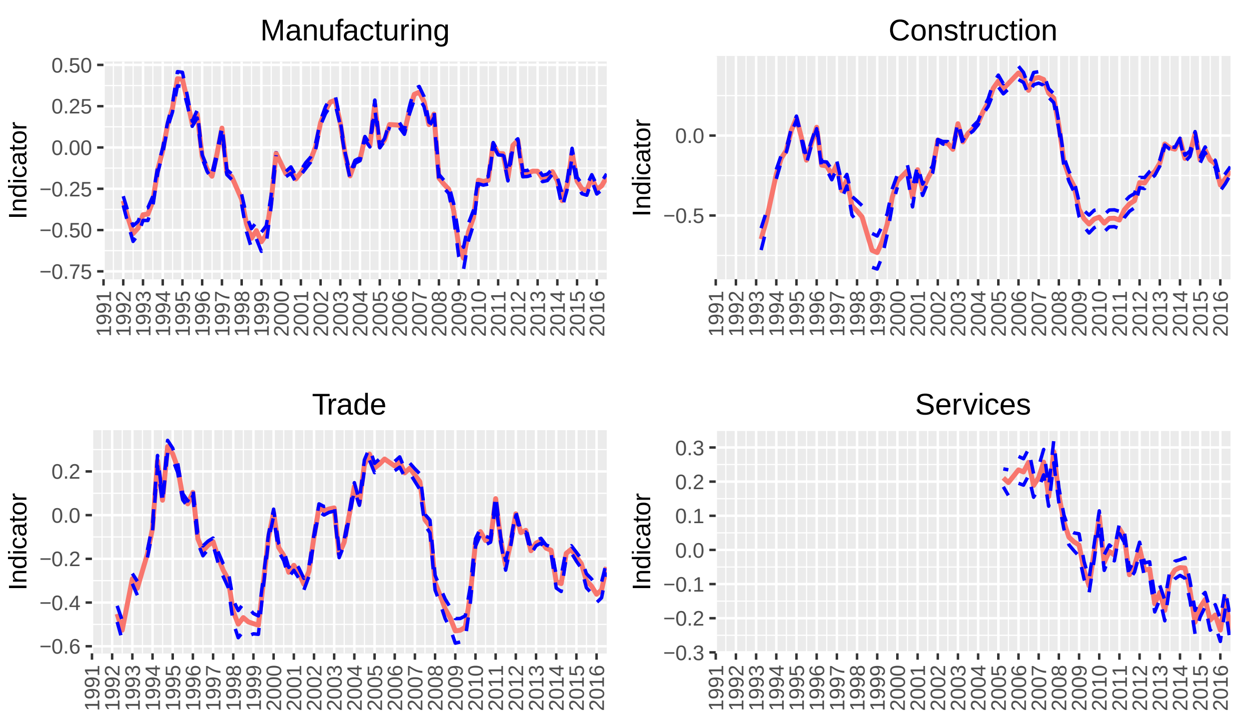

Figure 37: Sectoral confidence indicators with 95% confidence intervals

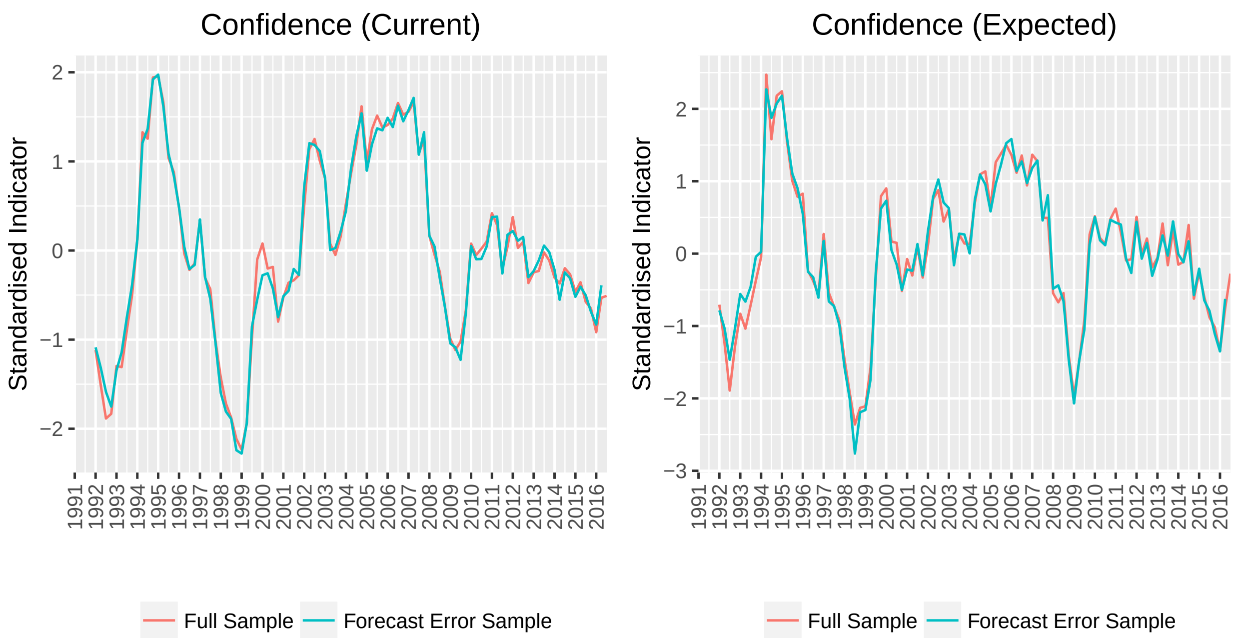

Figure 38: Confidence indicators based on the full and forecast error samples

Table 15: Correlations between indicators based on the full and forecast error samples

Indicator	Full-Stable Sample	Stable-RGDP Growth
Confidence (Current)	0.99***	0.76***
Confidence (Expected)	0.99***	0.68***
Dispersion	0.91***	-0.44***
Uncertainty (Combined)	0.96***	-0.31***

very similar to those for the full sample. The full sample measures, which do not rely on the panel structure, therefore seem to be robust to only calculating them using this smaller stable sample. This implies that the results are not driven by attrition rates.

1.10.2.2 Samples of firms that responded relatively frequently

Figure 3.40 reports the sample sizes for two relatively stable samples of firms, based on how frequently firms responded to the surveys. In the two versions, only firms that responded to more than 50% and to more than 75% of all the surveys over the period are included. Table 3.16 reports that the sample characteristics, in terms of firm size, are similar to those for the full sample, even though these stable samples are substantially smaller.

Figure 3.41 compares the full sample confidence indicators to the two sets of indicators based on the more stable samples. The confidence indicators based on these smaller samples seem to capture very similar trends, even though they are estimated which substantially smaller samples. This provides confidence that the results are not driven by the entry and exit patterns of firms.

Figure 3.42 compares the full sample uncertainty indicators to the two sets of indicators based on the smaller samples. The indicators still seem to point to similar periods of heightened uncertainty. However, there are a few instances where the indicators seem to differ, which is unsurprising

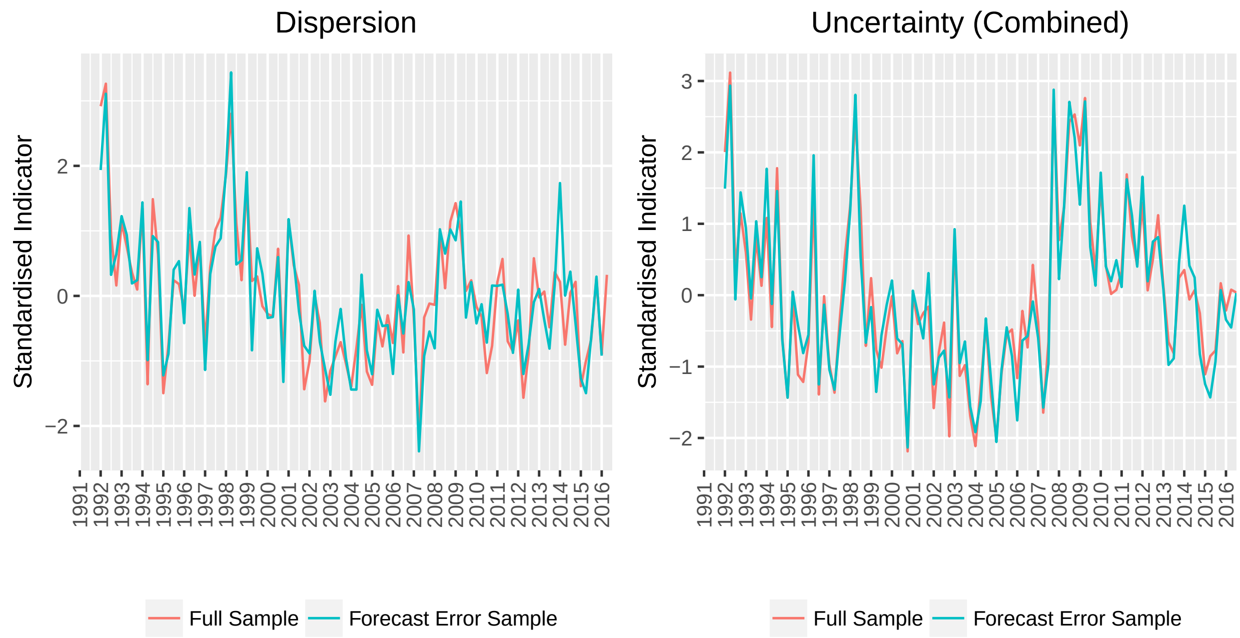

Figure 39: Uncertainty indicators based on the full and forecast error samples

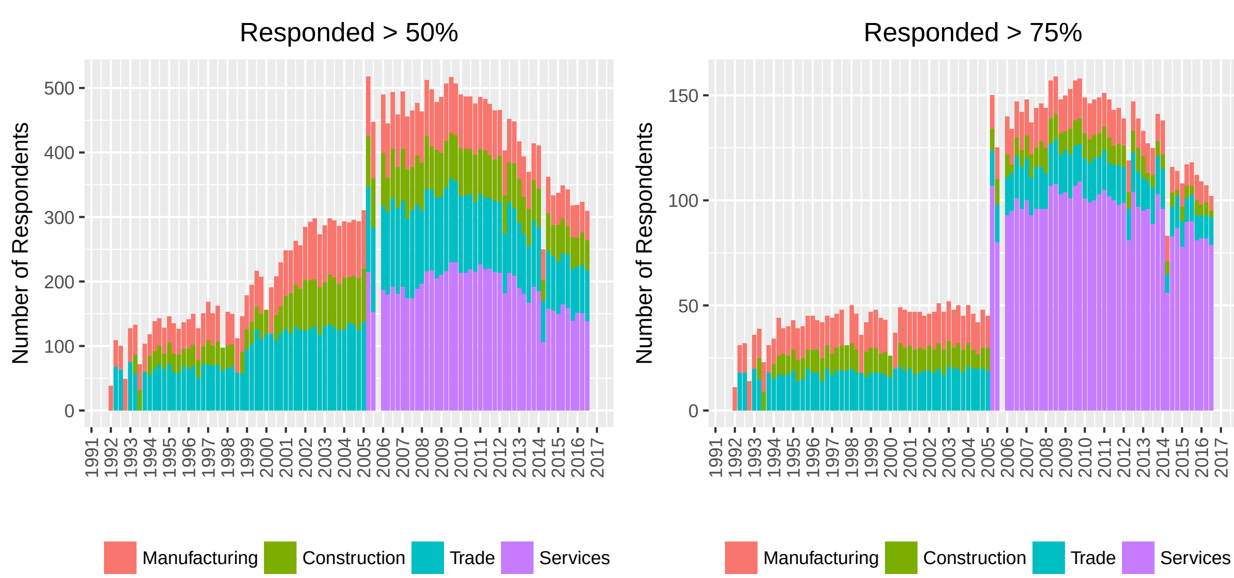

Figure 40: Number of respondents in the stable samples

Table 16: Sample characteristics in terms of firm size (full and stable samples)

Firm Size Category	Full Sample		Greater than 50% sample		Greater than 75% sample	
	Observations	Percentage	Observations	Percentage	Observations	Percentage
1	25,587	21.43%	5,504	18.67%	1,169	14.06%
2	15,288	12.80%	3,843	13.04%	1,232	14.82%
3	18,554	15.54%	4,328	14.68%	917	11.03%
4	13,717	11.49%	2,993	10.15%	724	8.71%
5	14,676	12.29%	4,888	16.58%	1,565	18.82%
6	9,140	7.65%	2,578	8.74%	867	10.43%
7	6,899	5.78%	1,819	6.17%	577	6.94%
8	6,894	5.77%	1,474	5.00%	491	5.90%
9	8,667	7.26%	2,053	6.96%	773	9.30%

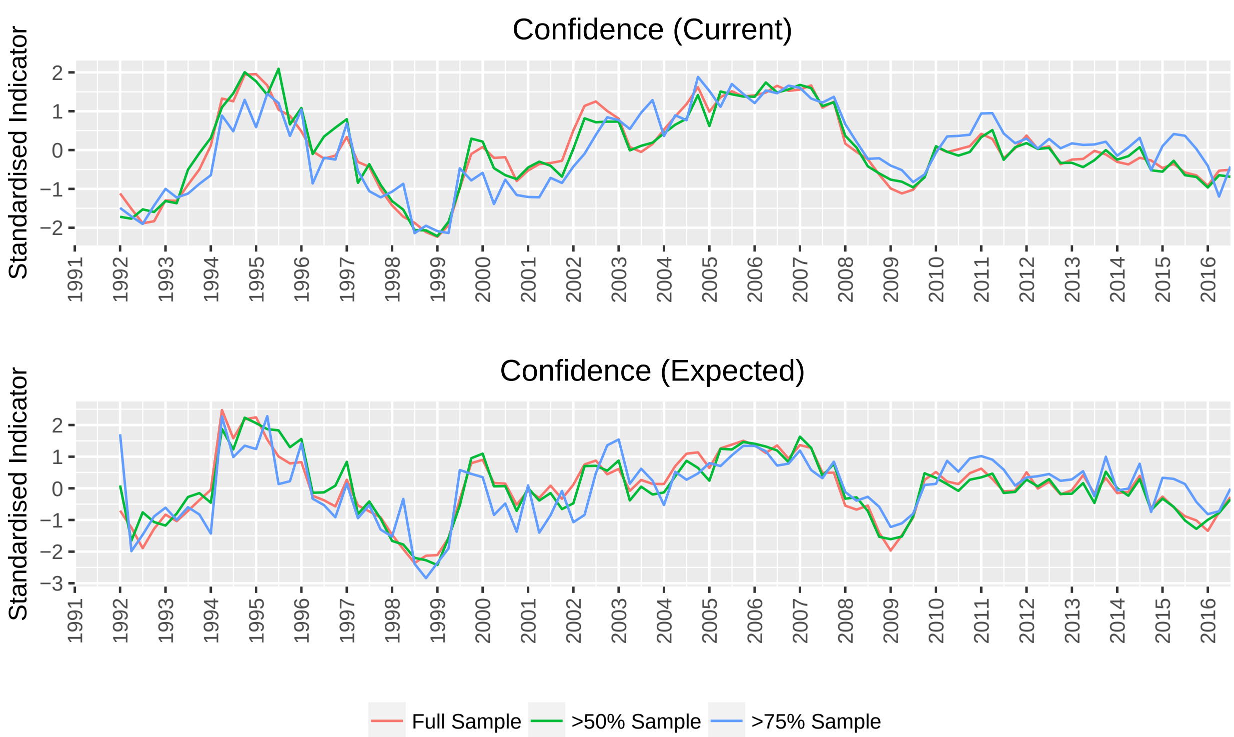

Figure 41: Confidence indicators based on the full and stable samples

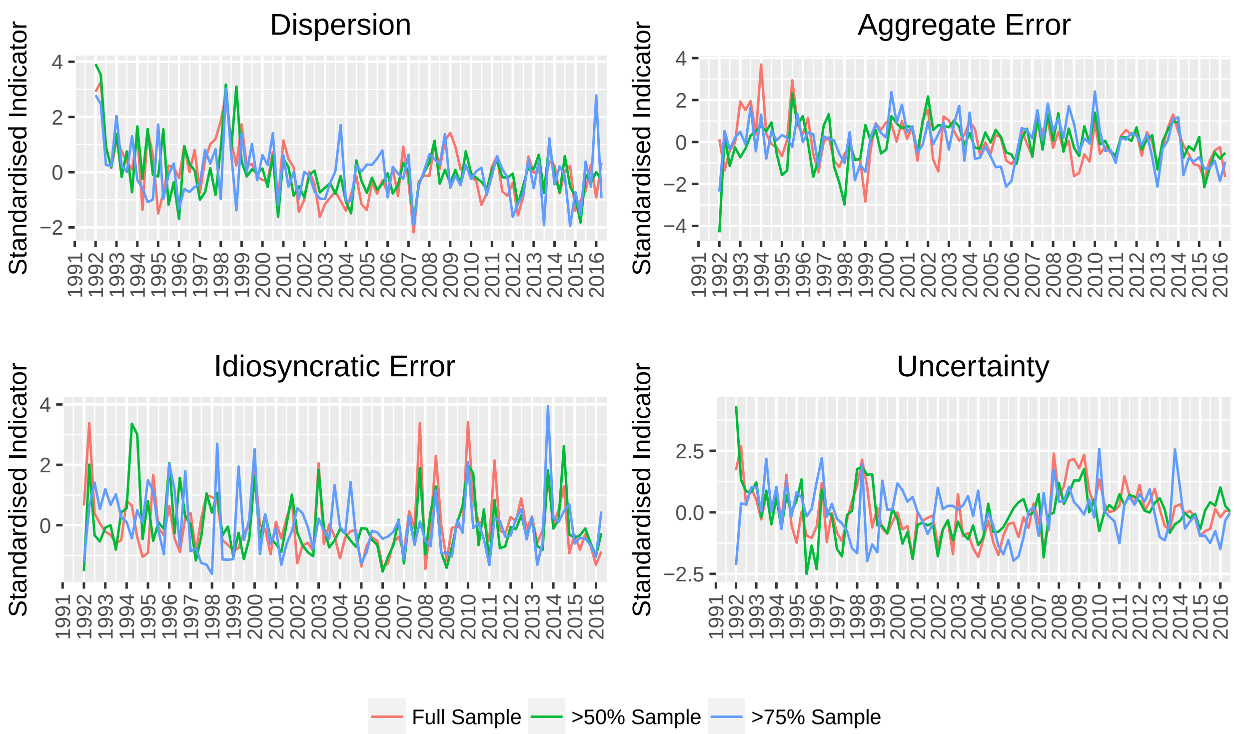

Figure 42: Uncertainty indicators based on the full and stable samples

given that the 'stable' samples are so much smaller. The combined uncertainty indicators from the smallest sample is the least similar to its full sample counterpart. This is because the PCA procedure exacerbates the differences in the indicators, as its factor loadings are not fixed.

Table 3.17 reports the correlations between the full sample indicators and their smaller sample counterparts, respectively. The correlations for the confidence indicators are high and significant, even for the smallest sample. The correlations are lower but still significant for the uncertainty indicators, even though these indicators are very volatile. Table 3.17 also reports the correlations between real GDP growth and the smaller sample indicators. The confidence indicators still exhibit significant positive correlations with real GDP growth, although the sizes are moderated. The dispersion indicators still exhibit significant negative correlations with real GDP growth. The same holds true for the larger sample (>50%) combined uncertainty indicator, although the correlation is not present for the smallest sample version.

The indicators therefore seem to be relatively robust to only calculating them for more stable samples. This is mostly the case even for the smallest sample, which includes fewer than 50 firms before 2005. This implies that these firms are driving a substantial part of the results, rather than the entry and exit of firms.

1.10.3 Unit Root Tests

The unit root tests for the series used in the VARs are reported in Table 3.18. The tests indicate that virtually all of the aggregate and sectoral indicators, and the corresponding real GDP growth rates, are stationary. The exception is confidence on current conditions in the services sector, which

Table 17: Correlations between indicators based on the full and stable samples

Indicator	>50% Sample		>75% Sample	
	Full Sample	RGDP Growth	Full Sample	RGDP Growth
Confidence (Current)	0.97***	0.77***	0.87***	0.65***
Confidence (Expected)	0.95***	0.66***	0.80***	0.50***
Dispersion	0.70***	-0.35***	0.45***	-0.23**
Aggregate error	0.46***	0.26**	0.52***	0.14
Idiosyncratic error	0.64***	0.00	0.38***	-0.02
Uncertainty (Combined)	0.67***	-0.42***	0.38***	0.00

Table 18: Unit root test statistics

	Total	**Manufacturing**	**Construction**	**Trade**	**Services**
Confidence (Current)	-2.76***	-2.81***	-1.85*	-2.63***	-1.05
Confidence (Expected)	-3.02***	-3.19***	-2.67***	-3.21***	-2.35**
Dispersion	-5.51***	-6.5***	-4.27***	-2.69***	-5.98***
Aggregate error	-5.36***	-8.13***	-4.08***	-6.42***	-4.48***
Idiosyncratic error	-7.28***	-5.73***	-4.53***	-5.93***	-3.54***
Uncertainty (combined)	-4.43***	-6.32***	-3.37***	-4.41***	-3.84***
Real GDP Growth	-2.13**	-4.65***	-1.96**	-2.33**	-3.84***

may be due to the relatively short sample period.

1.10.4 IRFs for the Confidence Indicators

This section reports the impulse response functions (IRFs) from bivariate VARs that include each of the other confidence indicators and real GDP growth. As before, the survey-based indicators enter in levels, while the SACCI BCI and real GDP series enter as annual quarter-on-quarter growth rates. The confidence indicators are ordered first in a recursive identification strategy, with the Cholesky decomposition used to identify structural shocks. The appropriate number of lags are selected by means of the AIC, the SC and the HQ.

Figure 3.43, Figure 3.44 and Figure 3.45 illustrate the IRFs from the VARs including confidence on expected conditions, the BER BCI and the SACCI BCI (in growth rates), respectively. The results are remarkably similar for the expected conditions confidence indicator and the BER BCI, whereas the SACCI growth rate exhibits a smaller significant relationship with real activity after two quarters. The IRF of the original BER BCI is slightly moderated compared to the IRF of the current conditions confidence indicator in the main text. This implies that firms are not necessarily responding to the published figures, although there may be some element of self-fulfilling prophecy in firms' decisions. It does suggests that the more robust confidence indicators are capturing some form of true or latent confidence.

1.10.5 Sentiment Indices

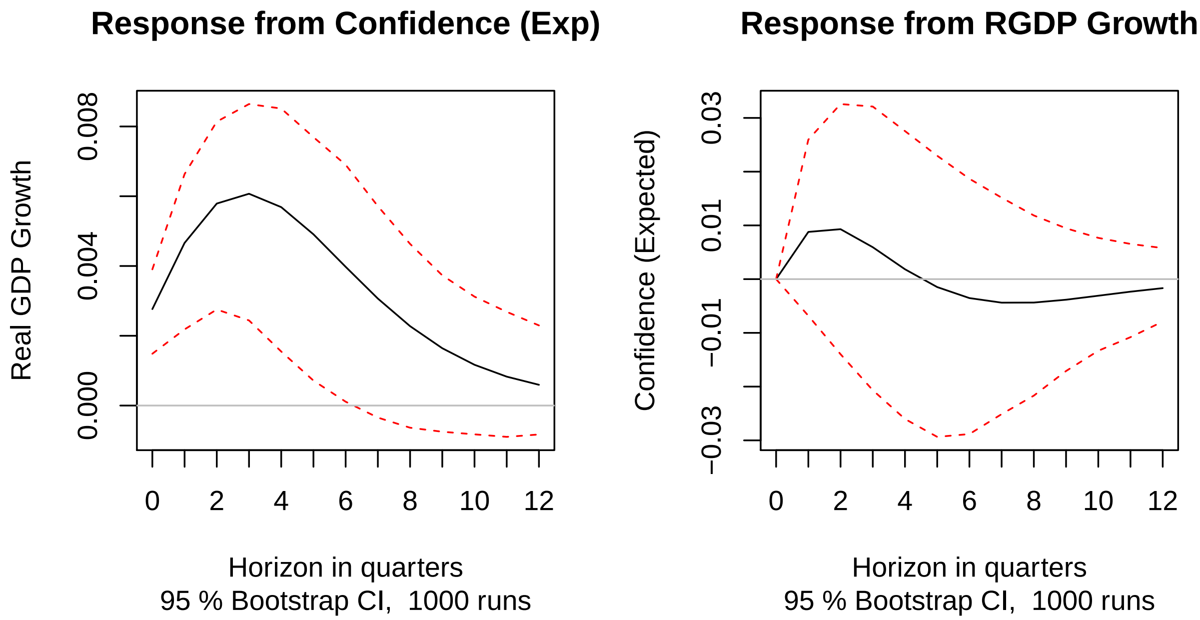

Figure 43: IRFs of confidence (expected conditions) and real GDP growth

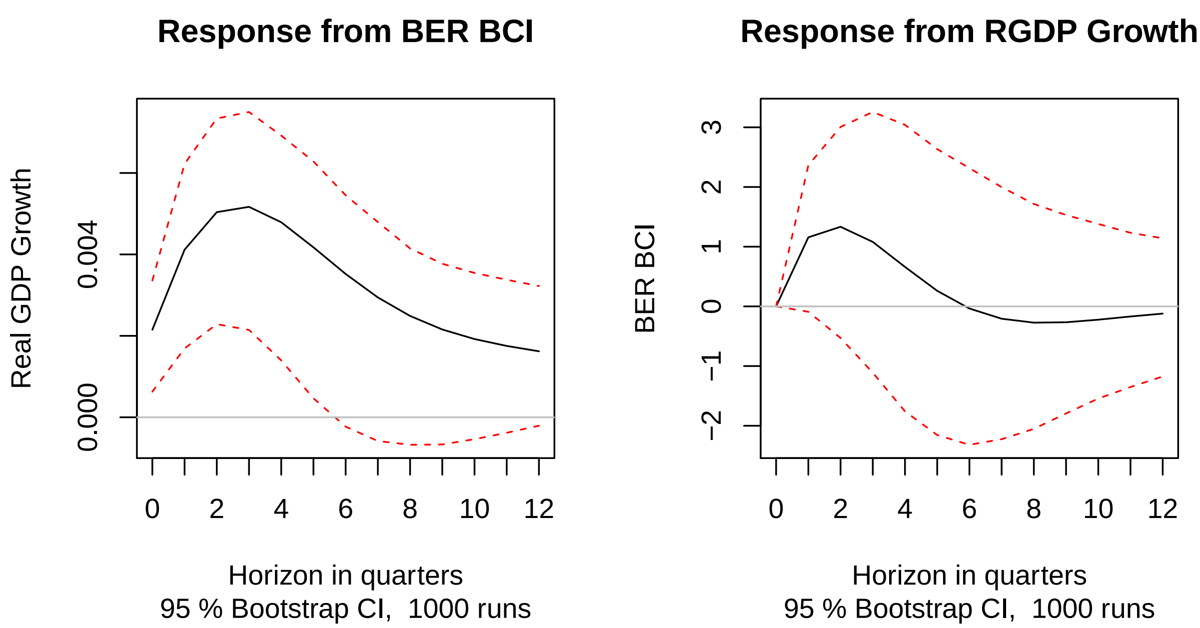

Figure 44: IRFs of BER BCI and real GDP growth

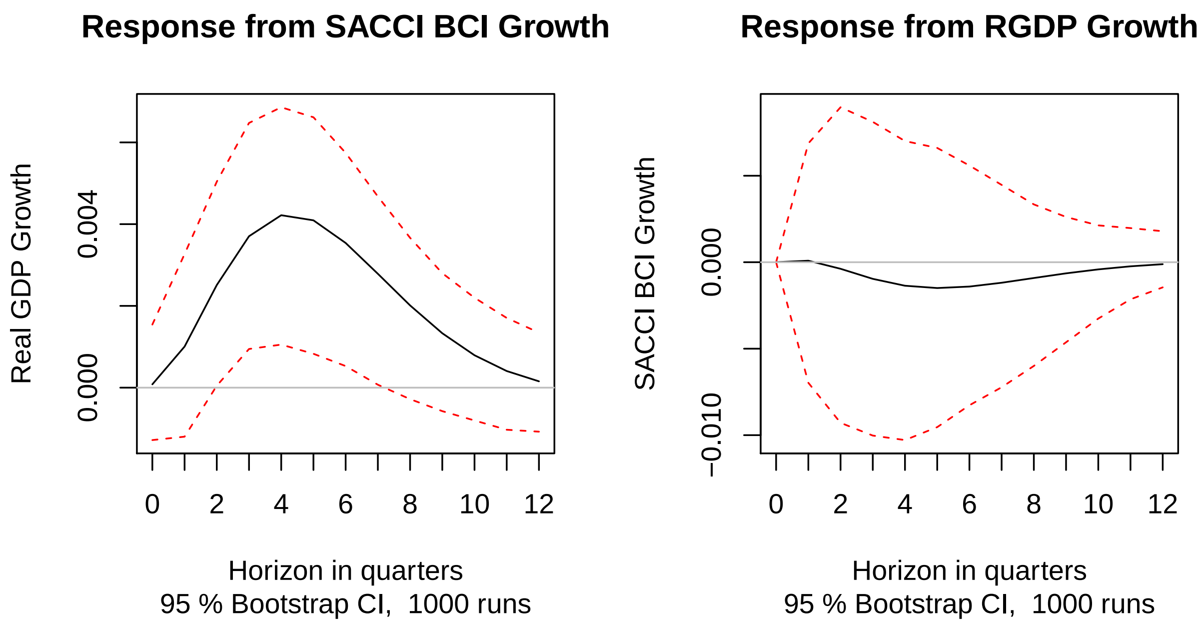

Figure 45: IRFs of SACCI BCI growth and real GDP growth

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Table 19: Sentiment indicators

Date	Confidence (Current)	Confidence (Expected)	Dispersion	Idiosyncratic_error	Aggregate_error	Uncertainty (Combined)
1992-03-31	-0.33	-0.15	2.92	0.13	0.65	2.00
1992-06-30	-0.42	-0.25	3.26	-1.35	3.39	3.12
1992-09-30	-0.50	-0.37	0.94	-0.41	0.40	0.35
1992-12-31	-0.48	-0.26	0.16	-0.04	0.06	1.15
1993-03-31	-0.37	-0.17	1.13	1.93	-0.21	0.60
1993-06-30	-0.37	-0.21	0.76	1.53	-0.32	-0.34
1993-09-30	-0.29	-0.15	0.36	1.95	-0.59	0.81
1993-12-31	-0.20	-0.09	0.10	0.36	-0.49	0.13
1994-03-31	-0.07	-0.03	1.35	3.70	0.80	1.08
1994-06-30	0.18	0.43	-1.36	0.39	0.65	-0.45
1994-09-30	0.17	0.26	1.49	-0.10	-0.39	1.78
1994-12-31	0.31	0.37	0.63	-0.25	-1.05	-0.60
1995-03-31	0.31	0.39	-1.50	-0.68	-0.92	-1.44
1995-06-30	0.25	0.26	-0.75	0.11	1.67	0.01
1995-09-30	0.12	0.16	0.24	2.94	-0.08	-1.11
1995-12-31	0.09	0.12	0.18	0.84	-0.34	-1.22
1996-03-31	0.00	0.13	-0.22	0.36	0.64	-0.66
1996-06-30	-0.10	-0.07	0.94	1.14	-0.44	1.38
1996-09-30	-0.14	-0.09	0.00	-0.58	-0.89	-1.39
1996-12-31	-0.13	-0.13	0.80	-1.44	0.25	-0.01
1997-03-31	-0.03	0.03	-0.74	0.01	0.40	-0.97
1997-06-30	-0.16	-0.12	0.44	0.22	-0.87	-1.37
1997-09-30	-0.19	-0.16	1.02	-0.90	0.22	-0.35
1997-12-31	-0.31	-0.19	1.20	-1.19	0.99	0.56
1998-03-31	-0.40	-0.29	1.86	-0.57	0.93	1.25
1998-06-30	-0.46	-0.37	2.80	-0.23	0.83	2.49
1998-09-30	-0.49	-0.45	1.13	-0.79	-0.50	1.22
1998-12-31	-0.54	-0.41	0.24	-0.85	-0.65	-0.71
1999-03-31	-0.57	-0.41	1.74	-2.84	-0.84	0.24
1999-06-30	-0.51	-0.31	0.23	-0.38	-0.76	-0.77
1999-09-30	-0.30	-0.09	0.30	0.89	-0.23	-1.02
1999-12-31	-0.12	0.12	-0.16	0.57	-0.04	-0.46
2000-03-31	-0.08	0.14	-0.28	0.94	1.93	-0.02
2000-06-30	-0.14	0.01	-0.32	0.85	0.02	-0.81
2000-09-30	-0.14	0.00	0.73	0.02	-0.14	-0.64
2000-12-31	-0.27	-0.12	-1.02	0.99	-0.96	-2.19
2001-03-31	-0.21	-0.04	1.15	0.15	0.11	0.01
2001-06-30	-0.17	-0.08	0.47	0.70	-0.44	-0.40
2001-09-30	-0.17	-0.01	0.17	-0.89	0.23	-0.25
2001-12-31	-0.16	-0.08	-1.44	1.07	0.82	-0.16
2002-03-31	0.01	-0.00	-1.01	1.54	-1.26	-1.58
2002-06-30	0.14	0.11	0.01	-0.84	-0.67	-0.80
2002-09-30	0.17	0.14	-0.42	-1.40	-0.58	-0.38
2002-12-31	0.11	0.06	-1.62	1.22	-0.86	-1.98
2003-03-31	0.07	0.09	-1.15	1.03	2.06	0.85
2003-06-30	-0.08	-0.04	-0.93	0.52	-0.62	-1.13
2003-09-30	-0.11	0.03	-0.71	0.06	0.02	-0.98
2003-12-31	-0.06	0.00	-1.04	0.35	-0.37	-1.69

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Date	Confidence (Current)	Confidence (Expected)	Dispersion	Idiosyncratic_error	Aggregate_error	Uncertainty (Combined)
2004-03-31	0.01	0.00	-1.40	0.97	-1.10	-2.11
2004-06-30	0.08	0.10	-0.81	0.63	-0.41	-1.29
2004-09-30	0.15	0.18	-0.14	-0.64	-0.19	-0.39
2004-12-31	0.24	0.18	-1.16	-0.02	-0.16	-1.43
2005-03-31	0.11	0.09	-1.37	-0.57	-1.37	-2.01
2005-06-30	0.19	0.21	-0.38	0.35	-0.68	-1.09
2005-09-30	0.22	0.23	-0.78	0.20	-0.40	-0.55
2005-12-31	0.19	0.25	-0.30	-0.88	-0.51	-0.48
2006-03-31	0.20	0.22	-0.72	-1.06	-1.37	-1.16
2006-06-30	0.21	0.18	0.15	-0.71	-1.28	-0.22
2006-09-30	0.25	0.22	-0.87	0.61	-0.59	-0.73
2006-12-31	0.22	0.15	0.93	-0.11	-0.39	0.42
2007-03-31	0.23	0.23	-0.34	-0.66	-0.89	-0.38
2007-06-30	0.25	0.21	-2.18	0.92	0.47	-1.65
2007-09-30	0.13	0.07	-0.33	0.50	-0.11	-0.65
2007-12-31	0.16	0.07	-0.12	1.00	3.39	2.76
2008-03-31	-0.06	-0.12	-0.14	-0.28	-1.45	0.77
2008-06-30	-0.11	-0.15	1.02	0.49	0.03	1.24
2008-09-30	-0.15	-0.12	0.12	-0.36	2.30	2.43
2008-12-31	-0.23	-0.28	1.14	0.06	-0.02	2.53
2009-03-31	-0.31	-0.38	1.43	-1.63	-1.17	2.10
2009-06-30	-0.33	-0.29	0.98	-1.47	-0.09	2.76
2009-09-30	-0.31	-0.19	0.08	-0.59	-0.03	1.02
2009-12-31	-0.24	0.03	0.24	-0.93	-0.16	0.34
2010-03-31	-0.08	0.07	-0.16	0.95	3.43	1.54
2010-06-30	-0.11	0.02	-0.32	-0.57	0.82	0.41
2010-09-30	-0.09	0.00	-1.19	-0.23	0.10	0.02
2010-12-31	-0.08	0.06	-0.77	-0.50	0.12	0.07
2011-03-31	-0.01	0.09	0.21	-0.80	-0.53	0.33
2011-06-30	-0.04	0.03	0.57	0.28	2.15	1.69
2011-09-30	-0.14	-0.04	-0.70	0.57	-0.18	0.83
2011-12-31	-0.09	-0.04	-0.85	0.35	-0.28	0.41
2012-03-31	-0.02	0.07	-0.38	0.43	0.28	1.30
2012-06-30	-0.09	-0.02	-1.57	-0.65	0.13	0.07
2012-09-30	-0.08	0.01	-0.89	0.47	0.89	0.50
2012-12-31	-0.17	-0.06	0.58	-0.01	-0.13	1.12
2013-03-31	-0.15	-0.03	-0.02	-1.10	0.29	0.13
2013-06-30	-0.15	0.05	0.07	-0.29	-0.58	-0.66
2013-09-30	-0.10	-0.05	-0.48	0.68	-0.17	-0.81
2013-12-31	-0.12	0.04	0.37	1.30	1.67	0.24
2014-03-31	-0.16	-0.05	0.22	0.49	0.02	0.35
2014-06-30	-0.18	-0.04	-0.75	-0.16	0.51	-0.06
2014-09-30	-0.14	0.05	0.05	-0.58	1.29	0.07
2014-12-31	-0.15	-0.14	0.22	-1.06	-0.92	-0.25
2015-03-31	-0.20	-0.07	-1.39	-1.13	-0.31	-1.11
2015-06-30	-0.17	-0.13	-1.00	-1.79	-0.81	-0.85
2015-09-30	-0.22	-0.18	-0.67	-0.91	-0.30	-0.78
2015-12-31	-0.24	-0.21	0.27	-0.41	-0.68	0.17
2016-03-31	-0.29	-0.27	-0.90	-0.25	-1.31	-0.22
2016-06-30	-0.21	-0.16	0.32	-1.67	-0.87	0.08
2016-09-30	-0.21	-0.07				0.04

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