

# Using Twitter to measure policy uncertainty in South Africa

**W Snyman**



**[orcid.org/0000-0001-9846-6586](https://orcid.org/0000-0001-9846-6586)**

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Supervisor: Prof WF Krugell

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Student number: 21698570

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## **ABSTRACT**

Policy uncertainty affects economies around the world through the impact that it has on employment, stock markets, consumption, inflation, production, investment, and exports, which ultimately affects economic growth. Due to these economic consequences, policy uncertainty has been receiving increased attention in recent years.

Since policy uncertainty impacts developing countries more severely than developed countries, it is an especially important concern to policymakers in countries such as South Africa. The South African economy — already affected by poverty, inequality, and high unemployment — is troubled further by an environment of high policy uncertainty that causes weak confidence and low economic growth.

The severity of the effects of policy uncertainty, not only in South Africa but all over the world, has highlighted the importance of addressing this issue. However, in order to be able to solve the problem of policy uncertainty, its causes, effects, and magnitude must first be understood. To facilitate an understanding of policy uncertainty, it is important that an accurate measure be obtained of the concept. This will provide support to economists and policymakers in terms of economic forecasting, evaluating the reception of policies and in implementing the lessons learned from previous policies.

In South Africa, the North-West University (NWU) has developed a policy uncertainty index (PUI) based on uncertainty in the news media, the Bureau of Economic Research's (BER) manufacturing survey and the expert opinions of leading South African economists about economic policy uncertainty. However, the rise of social media has provided a new source of data that holds numerous benefits for sentiment analysis, which include the fact that data can be acquired in real time; that communication takes place in a dialogue format which enables the public to directly voice their opinions; and that it is easily accessible and provides a larger pool of data than was previously possible with traditional sources, such as surveys.

This study used Twitter as a source of data to determine if social media can provide information about policy uncertainty in South Africa. This was done by calculating the correlation coefficients between measures of policy uncertainty derived from Twitter and various indicators of uncertainty, such as short-term interest rates, inflation, stock market prices, employment, investment, and household consumption. The Twitter uncertainty measures were also compared to two benchmark tests of policy uncertainty measures, namely Gross Domestic Product (GDP) and the NWU's policy uncertainty index.

The results were obtained via two methods of data analysis. The first method demonstrated that a Twitter measure of uncertainty coincides with occurrences of major political events, while the second method indicated that a Twitter measure of conviction has significant relationships with stock market

prices, employment, investment, and household consumption. The Twitter conviction variable also has a strong and significant relationship with GDP and, although no significant relationship exists with the second benchmark – the NWU’s policy uncertainty index – this is attributed to the low amount of data observations available for the index. Although among the various indicators of uncertainty the Twitter uncertainty measure only shows a weak relationship with the Consumer Price Index (CPI), a strong, significant relationship was found with the benchmark GDP. Based on the results from these two methods, a simple Twitter-based index was constructed to measure policy uncertainty from a South African perspective.

This study contributes to the knowledge base on policy uncertainty by showing that social media, especially Twitter, can and should be used to obtain information about policy uncertainty. In this regard, the recommendations to policymakers entail using measurements of policy uncertainty to judge the suitability and timing of their policy announcements and to make use of the functionalities provided by social media to mitigate policy uncertainty.

**Keywords:** South Africa, Social media, Twitter, Policy uncertainty, Measurement

## **ABBREVIATIONS**

ANC	African National Congress
ANCYL	African National Congress Youth League
ANX	Anxiety
API	Application Programming Interface
ARDL	Autoregressive Distributed Lag
ASGISA	Accelerated and Shared Growth Initiative for South Africa
ASX	Australian Securities Exchange
BER	Bureau for Economic Research
BDRC	Business Development Research Consultants
BRICS	Brazil, Russia, India, China and South Africa
CBOE	Chicago Board Options Exchange
CDE	Centre for Development and Enterprise
CPI	Consumer Price Index
DA	Democratic Alliance
DRC	Democratic Republic of the Congo
CSIR	Council for Scientific and Industrial Research
DBSA	Development Bank of Southern Africa
DJIA	Dow Jones Industrial Average
DSGE	Dynamic Stochastic General Equilibrium
EU	European Union
EY	Ernst & Young
FICA	Financial Intelligence Centre Act
FNB	First National Bank
FTSE	Financial Times Stock Exchange
FTSE/JSE ALSI	Daily prices of the FTSE/JSE All Share Index (JALSH)
GDP	Gross Domestic Product
GEAR	Growth, Employment and Redistribution

GfK	Growth from Knowledge
ICASA	Independent Communications Authority of South Africa
ICT	Information and Communications Technology
IMF	International Monetary Fund
JALSH	FTSE/JSE All Share Index
JSE	Johannesburg Stock Exchange
LIWC	Linguistic Inquiry and Word Count
MP	Member of Parliament
NATO	North Atlantic Treaty Organisation
NDP	National Development Plan
NEGEMO	Negative Emotions
NGP	New Growth Path
NHI	National Health Insurance
NSDS	National Skills Development Strategy
NUM	National Union of Mineworkers
NWU	North-West University
NWU-PUI	North-West University Policy Uncertainty Index
OECD	Organisation for Economic Co-operation and Development
POMS	Profile of Mood States
POPI	Protection of Personal Information
PWC	PricewaterhouseCoopers
RDP	Reconstruction and Development Programme
RICA	Regulation of Interception of Communications and Provision of Communication-Related Information Act
PUI	Policy Uncertainty Index
S&P	Standard & Poor's
SA	South Africa
SABS	South African Bureau of Standards
SAPS	South African Police Service

SARB	South African Reserve Bank
SARS	South African Revenue Service
SOE	State Owned Enterprises
SONA	State of the Nation Address
StatsSA	Statistics South Africa
SV	Stochastic Volatility
UN	United Nations
URL	Universal Resource Locator
USD	United States Dollar
VAR	Vector Autoregressive
VAT	Value Added Tax
VIX	Volatility Index
WITS	World Integrated Trade Solution
ZANU-PF	Zimbabwe African National Union – Patriotic Front

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# CHAPTER 1

## NATURE AND SCOPE OF THE STUDY

### 1.1 Introduction

#### *1.1.1 The impact of policy uncertainty*

The South African economy faces challenges of slow growth, high unemployment, poverty, and inequality. Data from the International Monetary Fund (IMF) show that over the past 10 years, growth averaged only 1.8% while the average unemployment rate was 25% for the same period (IMF, 2018a; 2018b). The latest statistics from Statistics South Africa (StatsSA, 2017a) show a Gini coefficient of 0.68% with 55.5% of the population living on R441 or less per person per month.

Moreover, in its semi-annual Monetary Policy Review, the South African Reserve Bank (SARB, 2017:1) warned that the outlook for domestic growth has worsened since 2016. The report stated that growth is not expected to exceed 1.5% in 2019, which is significantly lower than the National Development Plan's (NDP) objective of 5% growth in 2019 (SARB, 2017:2). The Monetary Policy Review attributes the dire situation of declining growth to political- and policy uncertainty, leading to reduced household consumption and stagnating investment (SARB, 2017:2).

Consequently, on 24 November 2017, the ratings agency, Standard & Poor's (S&P), downgraded South Africa's long-term local currency rating to BB+, or 'junk status', while the country's long-term foreign currency rating was downgraded from BB+ to BB. At this time, Moody's ratings agency kept their rating unchanged, but placed South Africa on review for a possible downgrade. S&P attributed the downgrade to the worse than expected condition of public finances caused by poor economic growth (Donnelley, 2017). The company stated that politics had played a significant role in this by encumbering economic policy (Donnelley, 2017). Moody's also highlighted political uncertainty as a major concern that is impeding the country's ability to stabilise government finances and confront the issue of low growth (Donnelley, 2017).

According to Mordfin (2014), there are three components to policy uncertainty:

1. Uncertainty about who will make policy decisions that will have economic consequences,
2. Uncertainty about what decisions will be made, and
3. Uncertainty about the effects of these decisions on the economy.

In South Africa, uncertainty about policies and their implementation has become a serious concern and an obstacle to economic development by causing low investor- and business confidence. As confirmed in the results from surveys by the Bureau for Economic Research (BER) and First National Bank (FNB), business- and consumer confidence levels in South Africa are at their lowest since the financial crisis of 2008 (FNB & BER, 2018). The BER's manufacturing survey shows that 76% of respondents stated political conditions, even more than weak demand and skills shortages, as the greatest obstacle to business (BER, 2017:14). While, in its Monetary Policy Review of October 2017, the SARB correspondingly affirmed that political uncertainty is the major cause of weak confidence and low economic growth in South Africa (SARB, 2017:17).

The effect of policy uncertainty on economic activity can, for example, manifest in the form of reduced consumer spending due to a precautionary saving motive, where households choose to spend less and save more in order to protect themselves against the effects of possible future shocks (Carroll & Kimball, 2006:8). Furthermore, under conditions of policy uncertainty, a decline in demand can lead to a reduction in output as risk-averse firms become unwilling to commit to investment- and hiring considerations (Kotzé, 2017:11).

The economic impact of policy uncertainty can also be observed through its effect on a country's exchange rate and financial markets (Krol, 2014:12; Liu & Zhang, 2015:104).

For instance, on 9 December 2015 the South African Rand reacted violently to former President Jacob Zuma's sudden decision to remove Finance Minister Nhlanhla Nene from his post, replacing him with the unfamiliar Mr. David 'Des' van Rooyen. This action led to outrage and uncertainty regarding the motives for the president's decision, giving way to protests and calls for him to resign.

Mr. van Rooyen's first speech as Minister of Finance caused the Rand to tumble further as uncertainty rose regarding his intentions to continue with the objective of fiscal discipline implemented by his predecessor. On 13 December 2015, the president replaced Mr. van Rooyen with a former Finance Minister, Mr. Pravin Gordhan. The consequences of this period of turmoil between 09 and 13 December 2015, was that the Rand lost 10% of its value over a four day period (Jammie, 2015).

The episode damaged the confidence of both local and international markets in the Rand and caused the currency to experience considerable volatility throughout January 2016, as the consequences of the event were deliberated. Uncertainty rose, resulting from concerns relating to:

1. Possible interest rate increases by the SARB in an effort to curb the inflationary effect of the Rand's losses,
2. A rise in the government's debt servicing costs owing to a rise in bond yields, which could result in higher taxes and lower government expenditure on social development and infrastructure, and
3. Possible further downgrades by ratings agencies.

On 24 June 2016, the Rand experienced its largest single-day loss since the 2008 financial crisis when the United Kingdom voted to leave the European Union (EU). The currency lost over 8% of its value against the United States Dollar (USD) due to global uncertainty regarding the impact of the United Kingdom's withdrawal from the EU and its possible effect on South African trade relations (Reuters, 2016). Globally, markets were abandoning currencies that were perceived as being risky and volatile against the USD. Adding to this, on 30 March 2017, former President Jacob Zuma dismissed Finance Minister Pravin Gordhan and replaced him with the former Minister of Home Affairs, Mr. Malusi Gigaba, after recalling Mr. Gordhan from an investor roadshow abroad. The incident again caused a depreciation in the Rand of 7% over a four day period (Sow, 2017). Another loss in value of 1.7%, in one day, followed on 8 August 2017 when the president narrowly won a motion of no-confidence in parliament (McClean, 2017).

The stock market reacted to the cabinet reshuffle of December 2015 in much the same volatile way as the Rand. On 14 December 2015, the Financial Times Stock Exchange/Johannesburg Stock Exchange (FTSE/JSE) Banks Index had lost 18.54% of its value, while the FTSE/JSE Financial 15 Index had dropped with 13.36% and the Johannesburg Stock Exchange (JSE) All Share Index had lost 2.94% (Mathews, 2015). The R186, the benchmark government bond, which had been trading at a yield of 8.66% at the start of the week, was trading at a yield of 10.40% at the end of the week (Mathews, 2015). Trading had become volatile, with 615 million shares changing hands as compared to the 183 million for the same period in the previous year (Newsclip, 2015).

The events of December 2015 show that the impact of uncertainty on financial markets can lead to significant fluctuations in the trade-level and price of assets. Price volatility has negative economic consequences as it creates an unstable investment environment, which can cause panicking investors to withdraw their funds and opt to look for less volatile investments elsewhere. This reaction serves to realise the initial losses and to spur further uncertainty in the market.

The impact of uncertainty on investments is important as investments in company shares contribute to a country's economic development by providing firms with the means to grow, enabling them to offer employment which aids in lower unemployment and higher economic growth. Investments, observed in terms of stock market fluctuations, react to new information in the form of investor optimism or pessimism, depending on the degree of market uncertainty and sentiment (Bird, Reddy & Yeung, 2014:3). While the negative effect of uncertainty on stock market prices manifest in the form of higher inflation and lower industrial production and lower exports (Irshad, 2017:94).

The impact of uncertainty on financial markets also affects pension funds causing them to lose value, which in turn means that the aging generation will be more dependent on younger generations, resulting in a financial burden on future economies.

The reactions of the Rand and financial markets to political events serve as examples of how economic policy uncertainty is damaging to the South African economy and highlights the importance of addressing the issue of uncertainty.

The South African Government needs to create an environment within which businesses can invest and employ, working towards the facilitation of higher economic growth, increased employment, poverty relief, and less inequality. Since 1994 South Africa has seen a range of macro-economic policy initiatives, from the Reconstruction and Development Programme (RDP), Growth, Employment and Redistribution plan (GEAR), Accelerated and Shared Growth Initiative for South Africa (ASGISA), and New Growth Path (NGP) strategies, to the recent National Development Plan (NDP), to name a few (Parsons, 2013:31). However, the publishing of such strategy documents has, to date, not generated significant growth or development and the numerous policy initiatives produced over the years create a list of mostly unsuccessful strategic plans (Parsons, 2013:32). Publishing strategy documents and formulating plans does not, of its own accord, foster growth and development.

Due to the fact that policy uncertainty is a major determinant of economic stability, it seems logical to attempt to accurately measure uncertainty for the purposes of forecasting and making correct judgements regarding possible economic outcomes.

### *1.1.2 The importance of measuring policy uncertainty*

The impact that policy uncertainty has already had on the South African economy and its possible future consequences highlights the importance of being able to accurately measure policy uncertainty. Measures of policy uncertainty provide assistance in economic forecasting, enable policymakers to gauge the reception of their policy proposals and help them to implement the lessons learned in the formulation of future policies.

Unfortunately, in recent years, certainty and trust have become very scarce, as evidenced by the results of the surveys conducted by the BER and FNB as well as the SARB's frequent references to the challenges that uncertainty imposes upon the South African economy. Thus, in order for policies to succeed and the economy to regain momentum, the issue of policy uncertainty in South Africa should urgently be addressed.

According to behavioural economics, emotions can significantly influence the behaviour and decision-making processes of an individual. Bollen, Mao and Zeng (2010:1) ask if this theory also applies to societies in general. Their study finds that an analysis of the average mood of Twitter participants can predict the stock market (Bollen *et al.*, 2010:1). This provides a basis for research regarding the use of social media to measure policy uncertainty. Since it has been proven that sentiment garnered from social media can predict the stock market, it can be inferred that social media could also provide valuable information regarding uncertainty.

The majority of policy uncertainty indices are based on newspaper reports mentioning policy uncertainty. However, newspapers are not the only way that the public obtain access to news anymore, as social media has become an important source of information; this is where opinions are formed, and this is where researchers can gain insight into the public's feelings about the news.

Various events point to the significant part that social media is increasingly playing in voicing public opinion and initiating political change. For instance, in 2011, social media played a part in the Arab Spring protests which forced rulers from power in Egypt, Libya, Tunisia, and Yemen (Brown, Guskin & Mitchell, 2012). Although the underlying drivers of the social unrest were exerted by exogenous political- and economic turmoil, social media helped to increase participation in civil protests (Dewey, Kaden, Marks, Matsushima & Zhu, 2012:41). In Latin America and Eastern Europe, social media, especially in the form of Twitter, has historically been used by civilian populations to raise awareness regarding key issues and to demand change (Cadena, Korkmaz, Kuhlman, Marathe, Ramakrishnan & Vullikanti, 2015:1).



Twitter is a social media platform that enables participants from all over the world to share stories and topics of interest, voicing their opinions in the form of direct statements on their own profiles or in the form of comments on statements by other parties. The platform is freely available to anyone with an Internet connection and is a popular low-cost social media option as it uses less mobile data, on average, than Facebook or Instagram (Duong, 2015). The ease and speed with which statements can be added to Twitter is one of the features that makes it an ideal forum to quickly share opinions and news. The platform also allows users to filter information by location and specific keywords, which is supportive of sentiment analysis.

The following statistics support the use of Twitter as a valuable source of data (Aslam, 2018):

- 335 million active monthly users.
- 500 million tweets sent per day.
- 80% of users on mobile.
- 100 million active daily users.
- The platform can accommodate 18 quintillion user accounts.

Although social media is often used to share news articles, it is also used to voice personal opinions by making statements and comments. To this end, research by Back, Stopfer, Vazire, Gaddis, Schmukle, Egloff and Gosling (2010:373) state that people are generally more honest about their feelings and opinions when posting on social media. This has led to the question of whether social media, in the form of Twitter, could offer a valuable input to policy uncertainty indices.

The remainder of this chapter will focus on explaining the problem statement and objectives of the study.

## **1.2 Problem statement**

Based on the discussions in the previous section, this study will examine whether existing policy uncertainty indices could be improved by incorporating social media, in the form of Twitter data, as an input to calculating a measure of policy uncertainty. The following section will state the general and specific objectives to be reached.

## **1.3 Objectives**

### *1.3.1 General objective*

The general objective of this study is to analyse the use of social media, in the form of Twitter, as a measure of policy uncertainty and an additional input into a policy uncertainty index.

### *1.3.2 Specific objectives*

In pursuit of the study's general objective, the following specific objectives are set:

1. To determine the feasibility of Twitter as a measurement of policy uncertainty by evaluating Twitter data trends against significant political events and accepted indicators of policy uncertainty,
2. To construct a basic policy uncertainty index, using the data obtained from Twitter, and to compare it with the existing South African policy uncertainty index, and
3. To provide guidelines to policymakers on how to respond to policy uncertainty, based on the insights gained from the first two objectives.

## **1.4 Conclusion**

This chapter discussed the impact that policy uncertainty has on the South African economy as seen through its effect on household consumption, investments, the exchange rate, employment, the stock market, and, ultimately, economic growth. This emphasised the importance of being able to accurately measure policy uncertainty. An introduction was made to the possibility of using social media as a measurement of policy uncertainty with specific reference to the Twitter platform.

The study continues with a literature study in Chapter 2, with emphasis on the definition of uncertainty; the economic importance of policy uncertainty; the causes of policy uncertainty; current methods of measuring policy uncertainty and the role of social media in economic forecasting. Chapter 3 focusses the discussion on South Africa in terms of policy uncertainty, social media usage, and Twitter, as well as the advantages and disadvantages of using Twitter as a source of data. Chapter 4 explains the methodology of the study and describes the data used, while providing a data analysis and discussing the results obtained. Lastly, Chapter 5 presents the conclusions reached, limitations of the study, and recommendations for future research.

## **CHAPTER 2**

### **LITERATURE STUDY**

#### **2.1 Introduction**

This study investigates the use of social media as a measurement of policy uncertainty. The aim of this chapter is to review existing research relating to policy uncertainty, its definition, importance, causes and measurement as well as the use of social media in academic research. The literature reviewed in this chapter will be used as the basis on which this study will continue in the subsequent chapters.

The purpose of this research is based on the three motives for research identified by Babbie (2011:95-97):

1. Exploration, which is done for three reasons:
  - a) To aid in the researcher's understanding of the subject and to satisfy his/her curiosity,
  - b) To determine the significance of conducting more intensive studies, and
  - c) To create methods that can be used in subsequent studies;
2. Description, in which a researcher observes events or situations and proceeds to describe what was observed; and
3. Explanation, which aims at providing an explanatory report of the results observed.

According to this framework of the various motivations for research, this study will comply mostly with that of exploration, although elements of the other objectives will be met throughout the study. In addition to being explorative, the study aims to build on the knowledge base of policy uncertainty in South Africa.

In this chapter, the definition of uncertainty will first be reviewed with the intention of clarifying what is meant by the term 'uncertainty' within the scope of this study.

Secondly, the economic importance of policy uncertainty will be examined with the purpose of providing a motivational background regarding the objectives of the study.

Thirdly, an overview of the causes of policy uncertainty will be presented which will serve as the contextual framework for measuring policy uncertainty.

Fourthly, leading research on policy uncertainty measurement will be reviewed with special attention to the models and methods used, as well as the existing knowledge base of policy uncertainty in South Africa.

Lastly, the role of social media will be reviewed as it relates to measuring economic indicators.

The sources utilised for the purpose of the literature study are:

- Academic Internet journal databases which include, among others: Google Scholar, ScienceDirect and the North-West University library's database,
- Online newspaper articles,
- Dissertations and theses on policy uncertainty,
- Government publications,
- SARB publications and
- Academic publications on research methodology.

## **2.2 Defining uncertainty**

According to a report by the North-West University's (NWU) School of Business and Governance (2016:1) released at the launch of their policy uncertainty index for South Africa, it is important to distinguish between risk and uncertainty. 'Risk' refers to a situation where the outcome is unknown but the odds of certain outcomes can be calculated accurately, while 'uncertainty' occurs when the information needed to accurately define the odds is indeterminable (NWU, 2016:4).

When looking at the definitions of risk and uncertainty and the distinction between the two, one cannot but look to the work of Knight (1921), from which the term 'Knightian uncertainty' was born which has become a widely accepted concept by economists, defining the unknown uncertainty. Knight (1921:231) defined risk by stating that it is a measurable uncertainty which can be made a quantifiable probability by grouping cases. To this extent, Knight (1921:233) distinguished between risk and uncertainty as follows: "The practical difference between the two categories, risk and uncertainty, is that in the former the distribution of the outcome in a group of instances is known (either through calculation a priori or from statistics of past experiences), while in the case of uncertainty this is not true, the reason being that the situation dealt with is in a high degree unique." Thus, according to Knight (1921:233), true uncertainty can be defined as circumstances where the possible outcomes and their probabilities cannot be estimated due to the lack of historical evidence relating to the current situation. It is this definition of uncertainty that will be used in the context of this study.

The primary focus of this study is economic policy uncertainty, which is uncertainty relating to monetary, fiscal and regulatory policy (Baker, Bloom & Davis, 2016:4). This type of uncertainty could impact economic growth through its effect on employment, government- and household expenditure, investment, inflation, production, exports and stock market volatility as seen in the following section (Agarwal *et al.*, 2018:3; Fedderke, 2004; Irshad, 2017:94; Kotzé, 2017:2; Moore, 2017:24).

### **2.3 Economic importance of policy uncertainty**

The importance of uncertainty is reflected in the way that it has increasingly been discussed by business executives and financial market participants (Kliesen, 2013:1). With regards to South Africa, this is evidenced in the SARB's Monetary Policy Review of October 2017, in which repeated references are made to uncertainty and low business confidence that causes household consumption to decline and business investment to diminish, ultimately leading to slow economic growth (SARB, 2017). Moreover, in this report of 60 pages, the word 'uncertainty' is mentioned 26 times, naming political instability as the central cause of low business confidence and uncertainty in South Africa (SARB, 2017).

Although policy uncertainty has received increasing attention, the negative impact thereof is not new (Fedderke, 2004). Fedderke's (2004) empirical research showed that uncertainty has historically had an extensive impact on investment in the South African manufacturing sector. The study found that uncertainty serves to create a lower threshold rate of return, below which it is improbable that investment will take place (Fedderke, 2004:28). From this, the study concluded that, in order to promote investment, policy makers need to create a stable, predictable economic environment without unexpected policy intervention (Fedderke, 2004:28).

Policy uncertainty not only affects investments, but is also a major determinant of capital flight (Fedderke & Liu, 2002:18). Fedderke *et al.* (2002:4) defines capital flight as capital that is unavailable for the purposes of domestic investment, and trade- and debt financing due to concerns relating to risk or uncertainty. Thus, capital 'flees' across borders to escape, or lessen, the risk or uncertainty of domestic markets. This is a key cause of concern to policy makers as capital in foreign countries is harder to tax, which could impede the ability of the country to maintain future debt repayments (Fedderke *et al.*, 2002:4). Capital flight also obstructs economic growth by reducing domestic resources for investment financing purposes (Fedderke *et al.*, 2002:1). This further highlights the negative impact of policy uncertainty on the economy.

Additionally, the NWU's School of Business and Governance (2016:4) stated that the extent to which negative shocks result in unfavourable situations and policy challenges is influenced by the environment and the institutional setting in which policies are formulated. The report highlighted the effects of policy uncertainty on economic activity through its impact on investments, where a rise in uncertainty increases volatility and reduces output (NWU, 2016).

To this extent, Aizenman and Marion (1991:23) presented evidence that policy uncertainty is correlated with economic growth but contend that the direction and strength of the correlation depend on the specific policy and the geographical area under examination. Similarly, a study by Dima, Dinca, Dima and Dinca (2017:66) supports the evidence that a rise in uncertainty results in an overall increase in economic volatility. This study concurs with Fedderke (2004) by concluding that economic growth is largely dependent on stable economic policy, devoid of surprises (Dima *et al.*, 2017:72). Policy uncertainty, therefore, has many negative economic effects.

These negative economic effects of policy uncertainty may be applicable to businesses, households, stock markets and interest rates. For instance, in one of the first attempts to thoroughly describe how business investment is affected by uncertainty, Bernanke (1983) found that macro-level factors, such as changes in monetary- and fiscal policies, could influence micro-level decision-making (for example a company's decision to invest in more staff or to expand its branches). He concluded that in situations of high uncertainty, businesses are deterred from investing by the possibility that new information will become available, especially in instances where the investments will be costly to reverse (Bernanke, 1983:21).

Policy uncertainty also affects households. However, before discussing the impact of uncertainty from the viewpoint of households, it is important to first clarify the terminology that will be used. Carroll *et al.* (2006:2) distinguished between the phrases 'precautionary saving' and 'precautionary savings', where 'precautionary savings' usually refer to the added wealth owned at a certain point in time as a result of past 'precautionary saving'. Thus 'precautionary saving' is defined as the present reaction of household expenditure to uncertainty (Carroll *et al.*, 2006:2). They proposed the use of the phrase 'precautionary wealth', instead of 'precautionary savings', to define the additional wealth owned at a certain point in time due to past 'precautionary saving' to avoid confusion (Carroll *et al.*, 2006:2). Precautionary wealth is not included in the scope of this study, but reference will be made to precautionary saving and it is therefore important to clarify the terminology used.

From a household perspective, Agarwal *et al.* (2018:3) showed that conditions of uncertainty lead to an increase in precautionary saving. The research by Agarwal *et al.* (2018:3) corresponds with that by Baur and McDermott (2012:10) and Flavin, Morley and Panopoulou (2014:153) by asserting that households tend to lower their participation in the stock market during times of uncertainty, by moving

to so-called safe haven assets such as gold and longer-term government bonds. This is evidenced by the volatile reaction of markets (for stocks as well as safe haven assets such as gold) to uncertainty (Baur *et al.*, 2012:15). According to Agarwal *et al.* (2018:33), during close gubernatorial elections in the United States, household participation in the stock market declined, but reversed after the election, except in cases where uncertainty is not resolved due to controversy regarding the party elected.

Linked to the effects it has on households, policy uncertainty may also affect stock markets. Stock market investments, as observed in terms of price fluctuations, react to new information in the form of investor optimism or pessimism, depending on the degree of market uncertainty and sentiment (Bird *et al.*, 2014:3). Additionally, Irshad (2017:94) showed that the impact of uncertainty on stock market prices usually spill over, leading to higher inflation and lower industrial production and exports.

Although there seems to be a clear link between policy uncertainty and stock markets, in terms of the relationship between uncertainty and interest rates, there exists some disagreement regarding the effect of policy uncertainty on interest rates. Hartzmark (2016:203), for instance, stated that higher uncertainty is related to lower interest rates in the long run, based on the precautionary saving motive. Although his study did not provide a clear explanation of this theory, a study by Guerrieri and Lorenzoni (2017) stated that consumers might react to a perceived contraction in their borrowing capacity by reducing their debt or increasing their savings. Thus, precautionary saving serves to heighten net lending, leading to a decline in the equilibrium interest rate (Guerrieri *et al.*, 2017).

On the other hand, Weatherson (2002) stated that a reduction in demand for investment may result from uncertainty as prospective investors become more cautious. This could lead to an increase in the demand for money and hence, an increase in interest rates (Weatherson, 2002).

However, according to Pflueger, Siriwardane and Sunderam (2017), a country's central bank will also determine the medium- to long term reaction of the interest rate to uncertainty, as the bank could choose to alter the interest rate in an effort to respond to inflation reactions.

Although there may be some disagreement about the relationship between policy uncertainty and interest rates, it is nevertheless apparent that policy uncertainty has an effect on a country's economy. This has been highlighted by various researchers such as Moore (2017:24), who found that under circumstances of high uncertainty, investment and employment are negatively affected, while the growth in household consumption of durable goods declines in favour of increased savings, in line with the precautionary saving materialisation of policy uncertainty. Similarly, Lensink, Bo and Sterken (1999) tested the effects of various types of uncertainty, such as export uncertainty, price uncertainty, and government policy uncertainty on economic growth. Their findings showed that uncertainty has a significantly negative impact on economic growth, especially in terms of policy credibility and export stability (Lensink *et al.*, 1999:10).

Furthermore, in a study of 21 countries, Brogaard and Detzel (2015:1) found that a 1% increase in policy uncertainty resulted in a decline in market returns of 2.9%, while market volatility rose by 18%. They contend that policy uncertainty and law-makers' indecision regarding policies have long-lasting, material financial consequences (Brogaard *et al.*, 2015:32).

These consequences, as Carrière-Swallow and Céspedes (2013:9) stated, may differ across countries and sectors, where countries that specialise in the production of durable goods, such as automobiles, furniture and machinery, will be affected by uncertainty in a higher degree. However, they also showed that emerging market economies react more severely to an uncertainty shock than advanced economies, in terms of the effect on investment and consumption (Carrière-Swallow *et al.*, 2013:19). They attributed the reason for this to the assumption that emerging market economies have less developed institutions and financial markets than developed economies (Carrière-Swallow & Céspedes, 2013:20).

Additionally, the IMF (2012:53) stated that the intensity of policy uncertainty can have an impact on how deep recessions can be, as well as on the force of economic recovery, where recessions with high levels of uncertainty, can be more acute and last longer, with slower recovery, than other recessions.

The literature reviewed for the purpose of this study provides evidence that the concept of uncertainty is a significant factor that affects economic activity through its influence on consumption, investment, employment, stock market volatility, inflation, production, exports, and, ultimately, economic growth. Considering this, the necessity to study uncertainty and its manifestations, causes, and methods of measurement is clear.

The following section reviews the causes of uncertainty with the intention of providing a background to the methods of measuring policy uncertainty.



## 2.4 Causes of policy uncertainty

As seen in Section 2.2, uncertainty occurs when the possible outcomes of a situation cannot be determined, making it impossible to define or calculate the probabilities of such outcomes (Knight, 1921:233). As was seen in the previous section, policy uncertainty has various effects on the economy. This section will review the most prominent literature regarding the causes of policy uncertainty.

The majority of the available work regarding policy uncertainty refers to Baker, Bloom and Davis, jointly, as well as in their individual capacities. They have made significant contributions to the understanding of policy uncertainty and developed an acclaimed policy uncertainty index for the United States in 2015, which has since been cited in almost all work regarding policy uncertainty.

The policy uncertainty index, developed by Baker *et al.* (2016:5), shows spikes in uncertainty during the Gulf Wars, close presidential elections, the 9/11 terrorist attacks, the 2008 financial crisis, the debt-ceiling dispute of 2011, and other disagreements regarding fiscal policy in the United States. According to an independent study by Bloom (2014), who worked with Baker to develop the index, policy uncertainty is sparked by three triggers, namely:

1. Major events, for example wars or terrorist attacks, as such events trigger a policy response which induces uncertainty since it is generally not clear what the response will be,
2. Elections, especially when they are close, as this heightens the inability to predict the outcome, and
3. Recessions, given that policymakers usually respond by making decisions to implement untried policies.

Bloom (2014) also stated that when governments are more polarised, the resulting government-level disagreements can lead to increased uncertainty. To this extent, Baker, Bloom, Canes-Wrone, Davis and Rodden (2014:7) concluded that polarised governments in the United States have less incentives to hold bipartisan votes to solve issues and obtain common ground.

Furthermore, Barrero, Bloom and Wright (2017:3) discerned between short-term uncertainty and long-term uncertainty in the United States by stating that short-term uncertainty is highly influenced by oil prices and exchange rates, while political risk has a larger impact on long-term uncertainty. Their research also showed that companies react to short-term uncertainty by reducing employment, while long-term uncertainty leads to a decline in investment in research and development (Barrero *et al.*, 2017:24). The sensitivity of investment to long-run uncertainty, relative to employment, is attributed to the fact that investment is more irreversible than employment (Barrero *et al.*, 2017:23)

An additional channel through which uncertainty can be augmented, was emphasised by DeMuth (2016) at the Elections, Policymaking, and Economic Uncertainty conference, where he stated that the way in which proposed policy changes are communicated to the public, can also spark uncertainty if the methods of reform is not clearly defined.

The above-mentioned research has shown that policy uncertainty can be brought about by a number of factors, including external events, such as wars and terrorist attacks, or situations originating from internal factors, for example policy disputes, elections, recessions, government division, and unclear communication.

The next section will review existing measurements of policy uncertainty in terms of the methodology and models used, with the objective of providing the background to the methodology used for this study. Emphasis will also be placed on the existing knowledge base regarding policy uncertainty in South Africa.

## **2.5 Measuring policy uncertainty: Current models and methods used**

Since the 2008 financial crisis, policy uncertainty has been receiving increased attention as economic activity underwent spells of growing uncertainty. Bloom, Kose and Terrones (2013:38) argued that this has been the cause of slow economic recovery. Additionally, according to Redl (2015:2), these spikes of uncertainty and their expected effect on economic recovery, have motivated the search for improved measures of policy uncertainty.

As mentioned in the previous section, one of the most prominent studies on measuring economic policy uncertainty was conducted by Baker, Bloom and Davis. They developed a policy uncertainty index for the United States by studying the frequency with which certain keywords appear in ten prominent United States newspapers. The articles were studied monthly to provide a count of the articles that contain the identified keywords (Baker *et al.*, 2016:5). The keywords chosen were placed in three categories, the first category contained words pertaining to 'uncertainty', while the second category consisted of words concerning the term 'economy', and the third category contained words regarding the term 'policy' (Baker *et al.*, 2016:5). In order to meet the objective of addressing economic policy uncertainty, an article must contain words from all three categories to be included in the study (Baker *et al.*, 2016:5). To evaluate their policy uncertainty index, they compared it to alternative measures of policy uncertainty, namely, other policy uncertainty indices, the frequency with which the Federal Reserve Bank's Summary of Commentary on Current Economic Conditions makes mention of policy uncertainty, and stock market volatility (Baker *et al.*, 2016:9). This policy uncertainty index has been accepted for use by various companies that specialise in data provision and has been the starting point of many policy uncertainty related studies since.

In the research by Bloom *et al.* (2013:39), a number of ways in which uncertainty is typically measured were identified and divided into two categories, namely: Measures that focus on uncertainty on a macro-economic level (for example, the frequency with which terms relating to economic policy uncertainty are mentioned in the media, the spread of employment forecasts, and stock market volatility); and micro-economic level measures, where the focus is on indicators of disparity in output amid different sectors (for example, firm stock returns, company sales and the spread of forecasts by managers from manufacturing companies) (Bloom *et al.*, 2013:39). The study focussed on macro-economic policy uncertainty by observing measures relating to economic policy and stock market volatility as follows:

1. Firstly, they considered the daily stock returns, which provide an indication of uncertainty relating to firm profits and prove to be a reliable measure for aggregate uncertainty (Bloom *et al.*, 2013:39);
2. Secondly, they incorporated the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) which conveys the expected volatility in equity price derived from S&P 500 index options (Bloom *et al.*, 2013:39);
3. Thirdly, they included the weighted average of: The number of tax provisions expected to expire in the near future, the frequency with which terms such as 'uncertainty' and 'economic policy' are used jointly in the media, and the forecasted dispersal of future inflation and government expenditure (Bloom *et al.*, 2013:39); and

4. Lastly, in order to obtain a measurement of uncertainty representative of a global scale, they applied the first measure to the six main advanced economies by making use of the longest available data series (Bloom *et al.*, 2013:39).

Similarly, the policy uncertainty index developed for South Africa by the NWU (2016:6-7) incorporated the frequency with which reference is made to economic policy uncertainty in the South African news media; the BER's manufacturing survey (of the extent to which political uncertainty is an obstacle to business activities); and the expert opinions of leading South African economists regarding policy uncertainty. They constructed a policy uncertainty index on a trial basis for the period of July to September 2015 which provided a base level of 50, indicating an increase in policy uncertainty when the index increases above 50, and a decline in policy uncertainty when it moves below 50 (NWU, 2016:7).

Hlatshwayo and Saxegaard (2016) also constructed a policy uncertainty index for South Africa in order to observe the effect of policy uncertainty on the exchange rate-export relationship. They obtained their data by collecting newspaper articles that mention words concerning 'economic', 'policy' and 'uncertainty' three times within 10 words from mentioning 'South Africa' (Hlatshwayo *et al.*, 2016:7). They found that their measure for economic policy uncertainty spikes during economic events where uncertainty is expected (Hlatshwayo *et al.*, 2016:9). However, they also found that, particularly in the more recent time-frame, policy uncertainty spikes occasionally occur when there are no economic upsets (Hlatshwayo *et al.*, 2016:10). A possible reason for this is that some of the articles captured may, for example, mention a decline in uncertainty but are still included in the sample as they contain the relevant keywords, leading to a false measurement of heightened uncertainty (Hlatshwayo *et al.*, 2016:11). Nonetheless, their results indicated that policy uncertainty coincides with lower export performance and that, in the absence of policy uncertainty, South African exports would be much more reactive to relative changes in prices (Hlatshwayo *et al.*, 2016:14-16).

Kotzé (2017) also conducted a study of policy uncertainty relating to the South African economy and found that an increase in fiscal policy uncertainty leads to a reduction in economic output with adverse effects on employment, consumption, investment, real wages, inflation, and marginal costs. The aim of the study was to observe the quantitative impact of fiscal policy uncertainty on economic activity, with the assumption that a sudden rise in volatility of a certain fiscal instrument is connected to an increase in policy uncertainty (Kotzé, 2017:2). Firstly, fiscal policy shocks were identified by specifying rules for each fiscal instrument, which include government expenditure, consumption taxes, income taxes, and capital taxes (Kotzé, 2017:2). Secondly, the method included independent shocks relating to the fiscal rules and the relevant fiscal processes by applying a stochastic volatility

(SV)<sup>1</sup> specification (Kotzé, 2017:3). A vector autoregressive (VAR) model was then used to combine a number of aggregate macro-economic variables with the measures of a sudden rise in fiscal policy uncertainty (Kotzé, 2017:3). The effect of an aggregate fiscal volatility shock on investment, wages, the cost of labour, consumption, output, nominal interest rates, and prices were then studied in terms of this model (Kotzé, 2017:3). Hereafter, the impulse response function was used to indicate that fiscal policy uncertainty shocks could be related to declines in investment, output and consumption as well as price increases (Kotzé, 2017:3). Finally, to analyse fiscal policy uncertainty in terms of a theoretically accurate framework, he constructed a dynamic stochastic general equilibrium (DSGE) model with inclusion of the specification of the fiscal rules in order to describe the impact of fiscal volatility shocks on the macro-economic variables (Kotzé, 2017:3). The model was then applied to South African data and the subsequent results showed that a sudden rise in fiscal policy uncertainty is related to a prolonged decrease in consumption, investment, economic growth, and employment as well as heightened inflation (Kotzé, 2017:3).

Brogaard *et al.* (2015) also conducted research regarding the measurement of economic policy uncertainty and stated that there are two traditional empirical methods of studying policy uncertainty. In the first method, researchers observe economic policy uncertainty in terms of events relative to the timing of policy implementation (Brogaard *et al.*, 2015:3). The second method measures economic policy uncertainty relative to elections (Brogaard *et al.*, 2015:4). Modern studies, such as that by Baker *et al.* (2016), Moore (2017) and the NWU (2016), include elements of both approaches by observing elections and other events relative to economic policy uncertainty.

Additionally, Moore (2017:2) identified three categories of proxies for policy uncertainty, namely: (i) those based on financial indicators, (ii) those based on forecasts by leading economists, and (iii) those based on media coverage. Moore (2017) tested all three methods and obtained the following results: (i) In terms of the first category, Moore (2017:4) used stock market volatility for the financial indicator measurement, as measured by the percentage change in price of the All Ordinaries index listed on the Australian Securities Exchange (ASX), consisting of 500 of the largest listed companies. He found that a major disadvantage of this method is that such measures are not directly linked to economic activity, and while company earnings are related to economic activity, the majority of the short-run change in price volatility is driven by alternative causes (Moore, 2017:4). He also found that the results were asymmetric; large gains in stock prices are uncommon while an increase in the stock price volatility measurement of uncertainty is accompanied by a large drop in stock prices (Moore, 2017:4). (ii) Moore (2017:6) also evaluated the dispersion of economic forecasters' views

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<sup>1</sup> 'Stochastic' is defined by English Oxford Living Dictionaries (2018a) as: "Having a random probability distribution or pattern that may be analysed statistically but may not be predicted precisely." It therefore means that SV models estimate volatility as a random variable (Gatheral, 2011:1).

regarding economic variables and found that, while this measure is closely related to economic activity, its major drawbacks are the shorter data history available in comparison to other measures and the possibility that it may show forecaster disagreement rather than actual uncertainty. (iii) Lastly, the newspaper-based method captured major events reasonably well and provided realistic results, but lagged behind the occurrence of events, which is attributed to the fact that the data was averaged on a monthly basis. He also states that false positives are unavoidable in this method where, for example, an article containing the word 'uncertainty' could be included in the data, although the content does not actually pertain to economic policy uncertainty (Moore, 2017:3). However, the automatically collected article samples highly correlate with the control group, which was selected manually, indicating that the false positives do not have a notable effect on the results (Moore, 2017:3).

Furthermore, Bloom (2009:2) stated that basic proxies of policy uncertainty include: stock market volatility, productivity growth, and the cross-sectional spread of firm- and industry-level earnings. Additionally, according to Kliesen (2013:1), policy uncertainty can be measured by the amount of cash held by firms on their balance sheets. This theory assumes that, when firms perceive the macro-economic environment to be too uncertain to accurately measure an investment's possible rate of return, they may choose to preserve their cash rather than to use it for the purpose of financing investment (Kliesen, 2013:2). This concept can be applied to the individual investor under the precautionary saving theory and, since research such as that by Agarwal *et al.* (2018:1) has shown that household participation in the stock market declines during periods of high uncertainty, the inference can be made that these savings are kept in the form of cash or other liquid assets.

Various studies, such as that by Baker *et al.* (2016), Brogaard *et al.* (2015,) and the NWU (2016), have compared the relationship between the frequencies of keywords obtained from traditional media sources and variations of the proxies mentioned (such as the occurrences of elections, other political events, recessions, stock market volatility, firm- and industry-level earnings, productivity growth, changes in cash-flows, investment, and employment) to derive a measure for policy uncertainty. However, policy uncertainty has only been granted significant attention since the 2008 financial crisis and there is still much discrepancy among researchers regarding the impact, measurement and causes of policy uncertainty. This is emphasised by Davis (2016) at the Elections, Policymaking, and Economic Uncertainty conference, where he stated that the causal link between the policy uncertainty index developed by himself, Bloom and Baker, and slow economic recovery from the financial crisis is not clear, since there is a possibility that other factors could contribute to slow economic growth.

Furthermore, Ozturk and Sheng (2018:276-277) provided critique of existing policy uncertainty measures as follows:

1. Stock market volatility as a measure of uncertainty: They assert that stock market volatility may not always be caused by uncertainty but could be attributed to financial stress or leveraging practices under conditions of low uncertainty.
2. The frequency of uncertainty-related references in newspapers: They argue that this measure leaves too much to reporters and editors, who may not be inclined to write about all events of consequence in terms of policy uncertainty.
3. The cross-sectional disagreement of economic professionals: They concur with the research by Lahiri and Sheng (2008:27) who found that disagreement is an effective measure of uncertainty under stable economic conditions but becomes unreliable in periods of instability with volatile aggregate shocks.

As a result, Ozturk *et al.* (2018:277) developed a model for measuring policy uncertainty which reflects the observed uncertainty of market participants, based on their subjective forecasts. They estimated variable-specific uncertainty measures based on eight economic indicators after which they measured country-specific uncertainty based on the weighted average of standardised constituents of the variable-specific measures (Ozturk *et al.*, 2018:277). They then constructed a global uncertainty index, as well as indices for 45 advanced- and developing countries and found that uncertainty is intensely countercyclical (Ozturk *et al.*, 2018:277). The economic indicators identified for the construction of their variable-specific uncertainty measures include: output, inflation, unemployment, investment, consumption, industrial production, and short- and long-term interest rates (Ozturk *et al.*, 2018:283).

Their findings show that uncertainty in almost all countries peaked around the recent financial crisis, even though a specific country may not necessarily have experienced a recession (Ozturk *et al.*, 2018:288). Furthermore, uncertainty in the majority of countries peaked more aggressively during previous recessions than the 2008 global recession (Ozturk *et al.*, 2018:288). To test their measure of policy uncertainty, Ozturk *et al.* (2018:289) observed the correlation of their uncertainty calculation to other uncertainty measures such as that by Baker *et al.* (2016) and Jurado, Ludvigson and Ng (2015). They found that their measure of policy uncertainty strongly correlates with that by Jurado *et al.* (2015) but has a weak relationship with the policy uncertainty index developed by Baker *et al.* (2016) (Ozturk *et al.*, 2018:289).

In their research, Jurado *et al.* (2015:1214) cautioned against overweighing the role of genuine uncertainty in movements of popular proxies for uncertainty and stated, as example, that in an environment of stable uncertainty, stock market volatility may change due to alternative factors, such as leveraging. They tested their theory by focussing on economic decision making and exploring whether the economy has become more or less predictable, rather than starting on the premise of determining if economic indicators have become more or less volatile (Jurado *et al.*, 2015:1178). Based on their findings, using measures of economic activity from two post-war datasets, they asserted that much of the movements in popular proxies for uncertainty are not driven by uncertainty (Jurado *et al.*, 2015:1180). However, their calculations do indicate a relationship between real economic activity and uncertainty, where uncertainty increases significantly during recessions (Jurado *et al.*, 2015:1214).

Lastly, in research by Arbatli, Davis, Ito, Miake and Saito (2017), a policy uncertainty index was developed for Japan based on the approach followed by Baker *et al.* (2016). They tested their results by estimating the correlations of their policy uncertainty index with existing proxies and measurements of policy uncertainty, such as stock market volatility, exchange rate volatility, and interest rate volatility (Arbatli *et al.*, 2017:2). By obtaining correlations with other common measures of uncertainty, they ascertained that their policy uncertainty index captures some of the significant causes of policy uncertainty (Arbatli *et al.*, 2017:2).

Measuring the causes and scope of policy uncertainty is challenged by the fact that many of the variables used for measurement are not independent variables. Volatility of the stock market may be an indicator and a cause of uncertainty, resulting in distorted observations where uncertainty could spike early in anticipation of an event or late as a reaction to an event, or the way in which the media portrays an event. Bloom *et al.* (2013:39) confirms this complexity, by stating that it is not an easy feat to measure policy uncertainty as it is a latent variable which is not in itself observable but must be inferred from other variables.

In summary, on review of the above-mentioned studies on policy uncertainty, the following frequently used measures have been identified: newspaper-based measures, forecaster disagreement, stock market volatility, the number of tax provisions expected to expire in the near future, volatility indices such as the United States VIX, expert opinions, productivity growth, the cross-sectional spread of firm- and industry-level earnings, the amount of cash held by firms, household saving and expenditure, employment, investment, interest rates, political events such as elections and policy announcements, inflation, and government expenditure. Economic growth- or activity, recessions, and other policy uncertainty indices are most often used as benchmarks with which to compare policy uncertainty indices constructed from combinations of the aforementioned measures of uncertainty.



This study will focus on macro-economic policy uncertainty by determining if social media, in the form of Twitter, can be used as another measure of policy uncertainty, while using several of the pre-identified variables to test the usability of the information provided by the new variable. The focus will also be on adding to the knowledge base of the measurement of policy uncertainty in South Africa.

The following section will review the use of social media in economic forecasting and its use and practicality as a source of data.

## **2.6 The role of social media in economic forecasting**

Social media is defined as: “Forms of electronic communication (such as websites for social networking and micro-blogging) through which users create online communities to share information, ideas, personal messages, and other content (such as videos)” (Merriam-Webster, 2018).

In recent years, the use of social media has become imperative to society. Most people are subscribed to, at least, one social media platform which they use every day. In their research, Kaschesky, Sobkowitz and Bouchard (2012:317) stated that social media is a pervasive and affordable form of communication that plays a major part in transforming societies and establishing interconnectedness. However, the large source of data generated by social media websites has remained mostly untapped and has only recently been gaining momentum as an area of interest (Asur & Huberman, 2010). With micro-blogging services, such as Twitter, social media enables the spread of information in the form of videos, images, and text from only a few users to audiences all over the world (Nisar & Yeung, 2018:102).

According to Kaschesky *et al.* (2012:317), social media is a valuable source of information in the field of policymaking where it can be used to determine the probable impacts of policies and to communicate the benefits expected. According to them, the democratisation of the web environment has increased the use of social media as a platform for voicing opinions (Kaschesky *et al.*, 2012:317). This has empowered citizens to become more actively engaged in topics, such as policy, as well as more demanding of their relationships with state institutions (Kaschesky *et al.*, 2012:317).

A study by Gefen and Ridings (2004) examined the reasons people publish in online communities and found that there are six major motivations, namely:

1. Exchange of information (to obtain or transfer information about a certain topic),
2. Friendship (to communicate with people),
3. Social support (to obtain and give emotional support),

4. Recreation (to be entertained),
5. Common interests (to discuss topics of common interest), and
6. Technical reasons (to use a functional interface and user-friendly search feature).

Research has shown that the communicative use of various types of media can, directly and indirectly, cause political participation (Gil de Zúñiga, Molyneux & Zheng, 2014:613). However, in comparison to traditional types of media, such as newspapers and television, the production time of social media is significantly shorter and the cost is much lower while requiring less physical effort from the user (Quintelier & Vissers, 2008:413). Gil de Zúñiga *et al.* (2014:613) also stated that, in addition to accessing offline content through an online medium, social media users also create their own original content which provides a new mechanism for political participation. Furthermore, according to Di Gennaro and Dutton (2006:311), the Internet can have a significant influence on the way that people participate in politics by increasing the ease with which they are able to communicate their political views.

Di Gennaro *et al.* (2006:312) also stated that the Internet could be an efficient tool to reach social groups that might otherwise be left out from the political process. To this extent, Gil de Zúñiga *et al.* (2014:616) theorised that all social interaction, including interactions beyond news and information gathering (for example communication with friends and family), can lead to political expression. From this, the assumption can be made that people can reveal their sentiment regarding certain public policies even when it is not explicitly the topic of their interaction on social media. However, Gil de Zúñiga *et al.* (2014:616) acknowledged that, although the potential is there for people to develop a 'political self' through interactions with different groups on social media, it is not certain that they will come in contact with a politically oriented group or be influenced enough to develop their own political identity. But since the potential is there, to obtain a clear picture of political expression, it could be worthwhile to study all interactions, and not only those that are explicitly political (Gil de Zúñiga *et al.*, 2014:616).

Östman (2012:1012) supports this view through a study that finds involvement in user generated content, both online and offline, to be predictive of political participation. This study observed the relationship between youth democratic engagement and involvement in user generated content (Östman, 2012). The results indicated that youth involvement in non-political user generated content, such as creating, publishing, and sharing information, significantly predicts political participation (Östman, 2012:1015). Östman (2012:1015) also found that involvement in user generated content is negatively correlated with political knowledge, while political participation is unrelated to political knowledge.

The attributes of social media that promote political expression, according to Gil de Zúñiga *et al.* (2014:627), are that it allows people to maintain connections to a variety of social groups and that it provides a space for self-expression which may include political expression.

Additionally, Kaschesky *et al.* (2012:317) stated that the need for recommendations and advice from online peer groups is strong, especially in terms of political matters. This is substantiated by Shearer (2016) who found that 24% of United States adults preferred using social media to gather and share information on political candidates in the 2016 United States presidential election. In terms of forecasting, Brown, Rambaccussing, Reade, and Rossi (2018) conducted a study to determine the usability of social media in predicting the outcomes of English Premier League soccer matches. They found that social media, in the form of Twitter, contain information not reflected in betting prices and can also aid in the interpretation of news during the matches (Brown *et al.*, 2018:3). Their research showed that the predictive power of social media is most significantly visible after events, such as red cards and goals, while the tone of tweets aids in interpreting information (Brown *et al.*, 2018:18).

The content of social media platforms is harvested by various sectors as valuable information for forecasting purposes. For example, financial firms use Twitter to predict market movements and design trading systems based on this information (Wieczner, 2015); the film industry use social media to determine marketing strategies for newly released films (Barnes, 2014); and the Australian Treasury launched an initiative in 2012 to mine Twitter data for use in economic forecasting (Ramli, 2012).

Social media has also been used as a source of data in sentiment analysis, which is defined by Nasukawa and Yi (2003) as the identification of sentiment expressions in texts with the aim of determining if these expressions are negative or positive regarding the subject. They isolate three topics of identification in sentiment analysis (Nasukawa *et al.*, 2003):

1. The expression of sentiment,
2. The strength and direction of the expression, and
3. The relationship of the sentiment to the subject, which is employed where the aim is to identify if a certain sentiment is expressed toward the entire subject or certain aspects of the subject.

A study by Bollen *et al.* (2010:2) showed that the public mood, derived from Twitter data, can predict the movement of the Dow Jones Industrial Average (DJIA). In their study, they derived the public mood from six observed dimensions from a sample of tweets collected between 28 February 2009 and 19 December 2009 (Bollen *et al.*, 2010:2). The tweets were collected based on the condition that it contained statements that reveal the author's mood such as 'I feel', 'I'm feeling', 'I am feeling', 'I am', 'this makes me', 'I'm', 'I don't feel', and 'makes me', after which they filtered the tweets to exclude messages containing spam (Bollen *et al.*, 2010:2). They then subjected the sample of tweets

to two computerised tools to determine the underlying mood, one which measured the overall positivity or negativity of the mood, and another that categorised the mood into six emotional dimensions, such as happy, kind, calm, alert, vital, and sure (Bollen *et al.*, 2010:2). After this, they tested the hypothesis that the public mood is predictive of the DJIA by means of the Granger causality test where they correlated the values of the DJIA with past values from the mood analysis tools and found that the null hypothesis (that the mood series does not predict future values of the DJIA) can be rejected (Bollen *et al.*, 2010:4). In order to validate the ability of the mood analysis tools to accurately capture the public mood, they compared the results to a time period containing several socio-cultural events which could have a significant impact on the public mood (for example the United States presidential election and Thanksgiving) (Bollen *et al.*, 2010:4). Finally, they constructed time series graphs to validate the measured mood against the expected mood responses; this showed that their mood series respond to important socio-cultural events (Bollen *et al.*, 2010:4).

Pagolu, Reddy, Panda and Majhi (2016) supported this by analysing the correlation between Twitter sentiment and stock market volatility and finding evidence of a strong correlation between the tone detected from tweets and the movements of the DJIA. Nisar and Yeung (2018) also investigated the relationship between political sentiment and price changes of the Financial Times Stock Exchange (FTSE) 100. They compared the movements of the FTSE 100 to a sample of 60 000 tweets, which they collected during the 2016 local elections in the United Kingdom, using three pre-identified keywords Nisar *et al.* (2018:102). Their findings confirm a correlation between the general public mood and short-term investment decisions, as well as causation between the sentiment derived from the Twitter keywords and price movements of the FTSE 100 (Nisar *et al.*, 2018:115-116). However, the study was limited by the fact that a small sample size prevented the results from being confirmed as statistically significant (Nisar *et al.*, 2018:114).

By performing sentiment analysis on tweets collected during 2008, another study by Bollen, Mao, and Pepe (2011:453) found that socio-economic events have significant effects on the public mood. They state that a specific mood can be expressed explicitly, for example when a person says that they feel angry, or a mood can be reflected in the types of words and characters used in the text (Bollen *et al.*, 2011:450). A current example of a mood not explicitly expressed but reflected by the types of characters and words used, would be if a person comments 'wonderful :-)' on a photo of United States President Donald Trump and North Korean leader Kim Jung Un shaking hands. Here the word 'wonderful' in conjunction with the 'smiley face' emoticon indicates joy or happiness. Bollen *et al.* (2011:450) hypothesised that all tweets collected over a certain time period can reveal changes in the public mood in general (Bollen *et al.*, 2011:450). Their study was based on two sets of data namely, a sample of tweets collected from Twitter over the period of 1 August 2008 to 20 December

2008 and a timeline of significant social, natural, cultural, political, and economic events that occurred in the same period in the United States (Bollen *et al.*, 2011:453). They used a psychometric instrument, Profile of Mood States (POMS), which categorises text in six mood dimensions, namely depression, anger, tension, fatigue, vigour, and confusion, to analyse the text obtained from Twitter (Bollen *et al.*, 2011:451). The results were graphed against the socio-economic events that occurred during the time period of observation for the purpose of evaluating their sentiment analysis tool (Bollen *et al.*, 2011:452). In order to determine the long-term effects of socio-economic events on public sentiment, they calculated Spearman Rank order correlations between the mood variables and found that socio-economic events are correlated with noteworthy fluctuations in the general public mood, although the effects are sometimes delayed (Bollen *et al.*, 2011:453).

Additionally, Bennett (2012:37) stated that the rise of social media has given way to a more personalised expression of political values where individual participation in politics have increased. He found that individuals mobilise towards economic causes that are of personal importance (for example environmental protection, fair-trade, developmental policies, inequality, and human rights) rather than collectively formed conventional group ideas (Bennett, 2012:21).

However, Bosch (2017:227) states that the use of social media as a discussion platform sometimes forms the agendas of mainstream news and supplements these sources. For example, Twitter discussions during the 'Rhodes Must Fall' (used on Twitter as #RMF) campaign were key resources to news media (Bosch, 2017:222). Therefore, content from social media should not be observed independent from traditional media sources (Bosch, 2017:230).

Nonetheless, social media does provide a useful way to determine public sentiment on various matters. Twitter, specifically, is the most commonly used source of data for sentiment analysis through social media. Asur *et al.* (2010) define Twitter by stating that it is an online social media platform used for micro-blogging, where the messages created are called tweets that are limited to 140 characters each and are displayed on users' timelines in a chronological order. The character limitation has since been increased to 280; however, during the data collection period, the 140-character limitation was still in effect.

The Twitter platform also provides in all of the above-mentioned major motivations that compel people to publish in social media, according to Gefen *et al.* (2004), such as: It is user friendly (technical reason); allows them to obtain information and to voice their opinions (information exchange); they can voice their feelings and receive community feedback (social support); they can find company (friendship) and entertainment (recreation), and they can talk and read about topics that interest them (common interest). A more detailed discussion on the use of Twitter as data will be provided in Chapter 3 (Section 3.4).

The literature reviewed here emphasise the significance of social media in general as a tool in sentiment analysis and economic forecasting. Some of the advantages of social media as a source of data can be summarised as follows:

1. It is a widely-used medium for voicing opinions and is affordable and easily accessible (Kaschesky *et al.*, 2012:317).
2. It provides a large data base that is still essentially untapped (Asur *et al.*, 2010).
3. It promotes the spread of information and the ability to obtain feedback, which allows researchers and the government, for example, to determine the public's expectation and opinions of policies (Kaschesky *et al.*, 2012:317).
4. It can aid in the interpretation of information in matters of public consequence (Brown *et al.*, 2018:18).
5. It can be used to predict stock market fluctuations (Bollen *et al.*, 2010).
6. It provides valuable information regarding the public's sentiment in terms of socio-economic events (Bollen *et al.*, 2011).
7. It can provide a more direct and refined view of public sentiment as it allows individuals to openly support specific causes rather than to be part of conventional groups that support a number of causes (Bennett, 2012).

The advantages and possible pitfalls of using social media for academic research purposes will be further discussed in Chapter 3 (Sections 3.4.1 and 3.4.2), with specific emphasis on Twitter in a South African context.

## **2.7 Conclusion**

In this chapter, the concepts of uncertainty, social media, sentiment analysis and Twitter have been defined. It has also been shown that policy uncertainty is an important economic factor, as it can impact interest rates and lead to lower levels of investment and household consumption, higher inflation, declines in industrial production and exports, lower employment, and, ultimately, lower economic growth. It has also been noted that the effects of policy uncertainty can vary across countries, where developing countries are more acutely affected by policy uncertainty than developed countries. Furthermore, policy uncertainty can also have an impact on the severity of recessions and the strength of economic recovery.

The causes of policy uncertainty were explored and include: external events such as terrorist attacks and wars, situations created by internal factors such as elections, recessions, and unclear communication by policymakers.

The main methods of measuring policy uncertainty were also reviewed and indicate that policy uncertainty is usually measured by collecting keywords from news sources relating to the terms 'economic', 'policy' and 'uncertainty'. The policy uncertainty measures are then compared to a variety of known indicators of uncertainty such as: Stock market returns, volatility indices, government expenditure, forecaster disagreement, the number of tax provisions expected to expire in the near future, household saving and expenditure, inflation, elections and other political events, investment, the amount of cash held by firms, expert opinions, the cross-sectional spread of firm- and industry-level earnings, interest rates, employment, and productivity growth. New policy uncertainty indices are also compared against benchmarks such as economic growth, recessions, and other policy uncertainty indices to test their efficacy.

An overview of the use of social media in economic forecasting has also been presented, showing that social media is extensively used to voice opinions. By using social media in this manner, citizens are encouraged to become more actively engaged in political topics as well as more demanding of government institutions. Various studies also found correlations between uncertainty derived from social media and stock market movements. Additionally, the motivations for using Twitter as a source of data in academic research have been stated.

The following chapter will provide a discussion of policy uncertainty as it relates to South Africa. The ability of South Africans to access social media, social media trends and the Twitter habits of South Africans will also be discussed. Finally, the advantages and disadvantages of using social media as a source of data for research in a South African context will be presented, with special focus on Twitter.

## CHAPTER 3

# MEASURING ECONOMIC POLICY UNCERTAINTY IN SOUTH AFRICA: A SOCIAL MEDIA PERSPECTIVE

### 3.1 Introduction

The aim of this study is to determine the use of social media, in the form of Twitter, as a measure of policy uncertainty. To this extent, this chapter provides an overview of the situation from a South African perspective as it relates to policy uncertainty and social media with specific emphasis on Twitter.

First, the impact of policy uncertainty on the South African economy is discussed and factors that could serve to increase policy uncertainty are identified. Secondly, the use of social media and certain obstacles that obstruct access to social media in South Africa are discussed along with the projects that are being implemented to improve the situation. Finally, the habits and preferences of South Africans in terms of Twitter are investigated by means of various online tools specifically designed to provide information relating to Twitter. The advantages and disadvantages of using Twitter for academic research purposes, in a South African context, is also discussed.

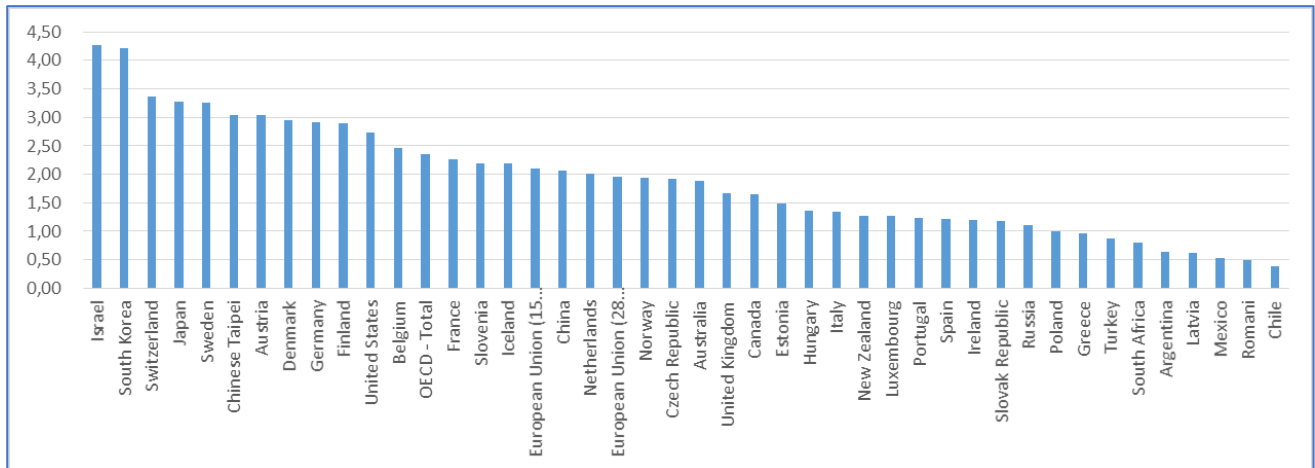
### 3.2 Policy uncertainty in South Africa

In the previous chapter, a study by Barrero *et al.* (2017) was reviewed which showed that the effect of short-term uncertainty on United States companies manifests in the form of a reluctance to employ new workers or to raise wages. This is also reflected in the South African context in that the unemployment rate has averaged 25% over the past ten years, as seen in Chapter 1 (Section 1.1.1). Another factor that is influenced by uncertainty is the willingness of companies to invest in research and development (Barrero *et al.*, 2017:24).

Research and development are vital to a country's economic growth. For example, Sokolov-Mladenović, Cvetanović and Mladenović, (2016:1016) found that an increase of 1% of gross domestic product (GDP) expenditure on research and development leads to an increase of 2.2% in GDP growth in 28 European countries. Using the latest available data, Figure 3.1 below compares the expenditure on research and development as a percentage of GDP of Organisation for Economic Co-operation and Development (OECD) countries, as well as key partner countries. It shows that



South African expenditure on research and development, as a percentage of GDP, was only 0.8% in 2015 in contrast to that of Israel and South Korea who spent the most on research and development (more than 4% of their GDP) (OECD, 2018a). Consequently, South Africa only had 1.3% growth in GDP in the corresponding year, while South Korea and Israel showed growth rates of 2.8% and 2.6%, respectively, for the same period (OECD, 2018b).



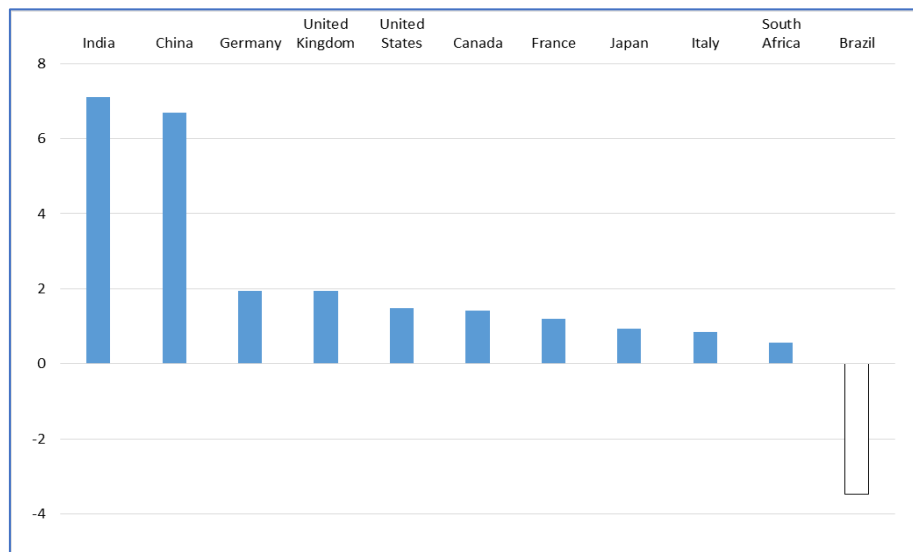
**Figure 3.1 Gross domestic expenditure on research and development as a percentage of GDP, 2015**

(Source: OECD, 2018a)

Fourie (2017) pointed out that the government is not the only entity that invests in a country's research and development. In South Africa, nearly a third of research and development expenditure is funded by the private sector (OECD, 2018a). Thus, the overall weak contribution to research and development could be remedied if the private sector were motivated to spend more in this area. However, according to Barrero *et al.* (2017:24), long-term policy uncertainty is a major obstacle to private sector investment in research and development. This also corresponds with the findings of the studies by Bernanke (1983), Kliesen (2013), Kotzé (2017), Moore (2017), and Nisar *et al.* (2018) (see Chapter 2), which indicated that increased policy uncertainty leads to decreased investment by the private sector.

Barrero *et al.* (2017:24) also found that both short- and long-term policy uncertainty manifest in the form of lower employment. To this extent, it is worth comparing South Africa's current unemployment rate of 27.4% to that of the countries who contribute the most to research and development in the sample. This comparison shows that South Korea and Israel have respective unemployment rates of 3.7% and 4.2%, which is considerably lower than that of South Africa (OECD, 2018c).

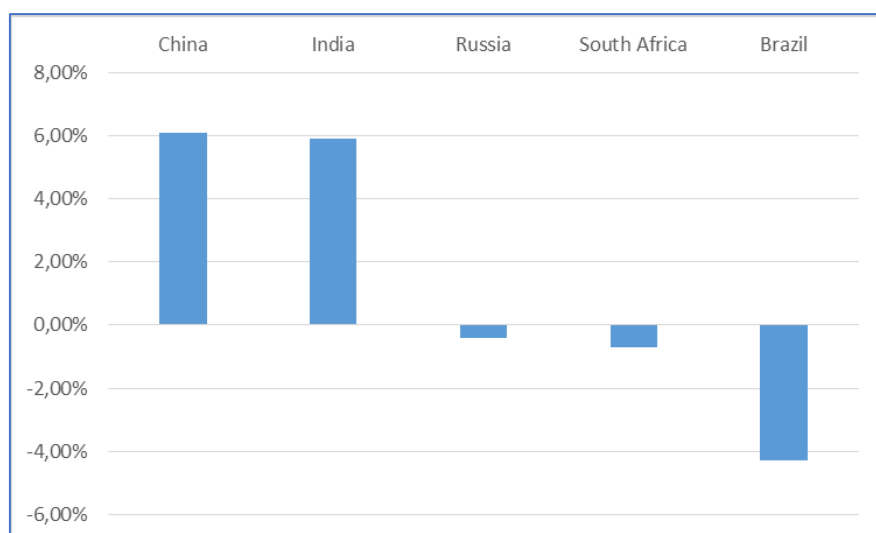
In its Monetary Policy Review of April 2018, the SARB stated that the high level of policy uncertainty, which had lasted since December 2015 when the finance minister debacle took place, has started to improve (SARB, 2018a:2). However, this comes after the economy had experienced only minimal growth of 0.6% in 2016 and entered a technical recession in late 2016 and early 2017 (SARB, 2018a:2). The report also stated that, due to the effects of policy uncertainty, investment contracted by 4.1% in 2016 while the South African economy lagged behind nearly all of the major economies that were experiencing economic expansion, as shown in Figure 3.2 below (SARB, 2018a:2).



**Figure 3.2 GDP growth: Comparison of South Africa to the ten major economies, 2016**

(Source: The World Bank & OECD, 2016)

Economic growth in South Africa also did not perform well in comparison to that of the other BRICS countries, as indicated in Figure 3.3 below.



**Figure 3.3 GDP growth: Comparison of South Africa to BRICS economies, 2016**

(Source: The World Bank & OECD, 2016)

At the start of 2018 there still remained policy uncertainty regarding the upcoming budget speech in February, possible further credit rating downgrades, and inflation that was pushing at the high end of the 6% benchmark (SARB, 2018a:4). Although inflation improved to 3.8% in March, it jumped to 4.5% in April when the increase in taxes, announced during the budget speech in February, started taking its toll (StatsSA, 2018a). In particular, the price of fuel has increased by 9% over the past year (StatsSA, 2018a), escalating the input costs of business and making it more expensive for the average South African to travel to work. The increase in value added tax (VAT), which reduced household disposable income, coupled with uncertainty regarding the exchange rate, leads to uncertainty about inflation and the measures that the SARB may take to curb it.

While it seemed in April 2018 as if policy uncertainty could be improving, the situation worsened again later in the year due to changes to policy in the mining industry and land expropriation. This was confirmed by the ratings agency Moody's in a statement on 26 June 2018 where it cautioned that growth prospects in South Africa will be constrained by low business confidence, whereas investors are concerned about uncertainty relating to land and mining reforms (Toyana, 2018).

The uncertainty about land expropriation started when President Cyril Ramaphosa announced plans to redistribute land without compensation in February 2018. The government is contemplating whether the Constitution should be amended to allow this. As Section 2 of the South African Constitution (1996) states: "This Constitution is the supreme law of the Republic; law or conduct inconsistent with it is invalid, and the obligations imposed by it must be fulfilled." While Section 25 of the Constitution (1996) states that: "Property may be expropriated only in terms of law of general application— (a) for a public purpose or in the public interest; and (b) subject to compensation, the

amount of which and the time and manner of payment of which have either been agreed to by those affected or decided or approved by a court.” Thus, if Section 25 of the Constitution is not amended, land expropriation without compensation could be seen as “law or conduct that is inconsistent” with the current Constitution. It is, therefore, not surprising that the proposal to amend the National Constitution has caused uncertainty, as it raises concerns regarding its dependability and the protection it provides to citizens and investors in South Africa.

At the same time, there has also been uncertainty regarding mining reforms in South Africa. Since the first discovery of diamonds in South Africa 151 years ago, the mining industry has been one of the country's main economic driving forces (Kane-Berman, 2017). South Africa is the world's top producer of platinum and the country's top five exported products are all commodities (World Integrated Trade Solution (WITS), 2016). However, the sector's contribution to GDP peaked in 1980 at 21%, after which it declined to 8% in 2016 (StatsSA, 2017b). The industry is fading, hindered by labour conflicts, falling commodity prices, and unaccommodating government policies.

A new mining charter is expected to be implemented within the coming weeks. A draft of the charter was released in June 2018 and approved by the Cabinet in September. However, the initial release of the draft was accompanied by much unhappiness and disagreement regarding its content, as it places a heavy regulatory burden on the industry that many feel may restrict investment and ultimately economic growth (Jeffery, 2018).

In addition to this, uncertainty is also linked to South Africa's current political climate. This reached a particular high point on 3 May 2018, when the new Public Enterprise Minister Pravin Gordhan stated at a meeting of parliament that South Africa has a reputation of unbridled corruption and unstable state owned enterprises (SOE's) (Dentlinger, 2018). He made this statement in a discussion regarding the damage caused by an alleged state capture, currently under investigation. This statement, and the fact that a state capture is being investigated, increase the risk of heightened uncertainty.

Although policy uncertainty has improved since the start of 2018, it has impacted the South African economy and it has had a profoundly negative effect on potential investment and economic growth. It is also possible that uncertainty could unexpectedly rise again to obstruct economic progress. To address the issue of policy uncertainty, with the aim of preventing its damaging effects, it is important to be able to properly measure it. By obtaining an appropriate measure for policy uncertainty, it will be possible to determine public sentiment regarding certain policies, to adapt future policies accordingly, and to prepare the economy for possible situations where uncertainty is unavoidable with the aim of preventing economic shocks.

The objective of this study is therefore to determine if policy uncertainty measures could be improved with the inclusion of social media, such as Twitter data. In keeping with this goal, the following section will discuss the trends and usage of social media in South Africa.

### **3.3 Social media usage in South Africa**

A study by the market research company, World Wide Worx, and the brand intelligence company, Ornico, showed that South Africans have significantly increased their overall use of social media from 2016 to 2017 (Ornico & World Wide Worx, 2017). The report indicated usage increases in the major social media platforms as follows (Ornico *et al.*, 2017):

- Facebook: Increased from 14 million users in 2016 to 16 million users in 2017
- Twitter: Increased from 7.7 million users in 2016 to 8 million users in 2017
- LinkedIn: Increased from 5.5 million users in 2016 to 6.1 million users in 2017
- Instagram: Increased from 3.5 million users in 2016 to 3.8 million users in 2017

The report stated that Facebook is becoming a significant rival to radio and television in terms of public reach, while Twitter remains the most popular platform for engagement in public discourse (Ornico *et al.*, 2017). Twitter's popularity is attributed to the access it provides to news, celebrity gossip, and debates, while enabling users to contribute their own opinions; this leads to robust growth in user engagement, even though the platform's user growth, overall, is slow (Ornico *et al.*, 2017). Additionally, a study by Hootsuite and We Are Social (2018) showed that, overall, 32% of South Africans are active social media users.

Before proceeding, it will be meaningful to provide a definition of the term 'hashtag' as defined by English Oxford Living Dictionaries (2018b) in terms of its use in social media: "A word or phrase preceded by a hash sign (#), used on social media websites and applications, especially Twitter, to identify messages on a specific topic." A 'hashtag' therefore makes it easier for users to find all the social media posts related to a specific topic.

In their report on the social media outlook for South Africa in 2017, Ornico and World Wide Worx (2016) stated that social media has gained momentum as a tool for public activism. An example of this was the hashtag definition of one of the country's most notorious campaigns, #FeesMustFall, which started at the University of Witwatersrand and spread to universities all over the country in 2015. Another campaign that gained momentum through a hashtag definition on Twitter was #SayNoToXenophobia which aided in the mobilisation of a march of over 10 000 people against xenophobic attacks on foreigners in 2015 (Workman, 2017). South African citizens also assembled

in a protest against then President Jacob Zuma in December 2015 under the hashtag #ZumaMustFall, after he dismissed two finance ministers in less than one week. The report by Ornico *et al.* (2016) stated that almost all present-day campaigns and causes are established with a hashtag.

The growth in popularity of political campaigns channelled through social media has been labelled as 'hashtag politics' (Wasserman, 2018). As discussed in previous sections, South Africa has become very familiar with hashtag politics. While official decisions, announcements, and analyses are still made via traditional news media, social media is becoming a significant source of real-time news. Although many of the hashtag campaigns have led to destructive and inconvenient protests, based on Östman's (2012) research, discussed in Chapter 2 (Section 2.6), the political culture of South Africans may have been deepened through expressions of indignation or the sharing of jokes and gossip on social media.

The Council for Scientific and Industrial Research (CSIR) provides another example of how social media is used in South Africa. The organisation is currently conducting a project where social media is observed in order to detect crime trends (Vermeulen, 2018). They aim to obtain and analyse data from Twitter and to classify events according to frequency, area, and type (Vermeulen, 2018). Additionally, various South African government departments and parastatals (for example the Office of the President, the SARB, and the South African Revenue Service (SARS) make use of social media, such as Facebook, Twitter, and YouTube, to communicate with the public and to promote policy comprehension (South African Government, 2018). While, in October 2017, the South African Minister of Police, Mr Fikile Mbalula, launched the #MyPoliceStation campaign that enables the public to report service delivery complaints via the social media platform Twitter South African Police Service (SAPS), (2017). Many South African politicians also have social media accounts in their personal capacities where they share information and opinions, such as President Cyril Ramaphosa, Helen Zille of the Democratic Alliance political party, and Mbuyiseni Ndlozi of the Economic Freedom Fighters political party. This demonstrates how South African politics have become increasingly immersed in social media.

However, almost no social media platform can be used without an Internet connection. It is therefore worth discussing access to Internet in South Africa to provide a clear picture of how available social media is to the South African public.

According to the World Bank (2018), 54% of the South African population is using the Internet. However, a report by Freedom House (2017) indicated that internet access in South Africa is not without obstacles. The report singled out two new legislative proposals that have the potential to restrict the freedom of internet access in South Africa, namely, the Cybercrimes and Cyber Security

Bill that has been criticised for potentially threatening privacy rights and freedom of expression; and the Film and Publications Amendment Bill, criticised for giving the government far-reaching powers in terms of content censoring, which could affect communication of individuals on social media (Freedom House, 2017).

At the same time, public policy relating to the protection of Internet users is still developing, for example, the Protection of Personal Information (POPI) Act, which was signed by former President Jacob Zuma in November 2013, is expected to come into effect during the coming months (Freedom House, 2017). The Act focusses on the protection of personal data, online security, and privacy.

In terms of location, internet access is skewed towards urban areas (Freedom House, 2017). Although 57% of users access the Internet via mobile devices, the situation for citizens living in rural and informal communities is aggravated by the Regulation of Interception of Communications and Provision of Communication-Related Information Act (RICA) This Act requires mobile users to provide proof of physical address along with a copy of their identification document to subscribe to a mobile network (Freedom House, 2017). This poses a potential obstacle to the use of mobile phones to people who live in informal settlements (Freedom House, 2017).

Another factor that obstructs access to Internet in South Africa is the cost of data. South Africa ranks 93<sup>rd</sup> in the world in terms of broadband pricing according to research by BDRC (Business Development Research Consultants) Continental and Cable.co.uk (2018) and 13<sup>th</sup> in Africa according to Research Information and Communications Technology Africa (2017). In 2016 the #DataMustFall campaign was started as a protest against the high costs of out-of-bundle data charges and short data expiry periods. Mr. Maleka, spokesperson for the Independent Communications Authority of South Africa (ICASA), attributed the high data costs to limited spectrum availability that prevents market entry of new companies and limits competition (Nebula, 2018).

However, affordable Internet access of a good quality among low income communities is growing, due to Wi-Fi subsidised by the government in initiatives, such as Project Isizwe, all over the country (Freedom House, 2017). Project Isizwe works with the government to establish free internet zones for low income communities with the aim of education, promotion of social inclusion, and economic development (Project Isizwe, 2018). Furthermore, the introduction of Facebook Lite and Twitter Lite has made social media more accessible to low-income communities as these applications use less data to install and are accessible even with poor network coverage.

In spite of regulatory and structural barriers to the use of mobile networks and data in South Africa, Internet access is advanced by the emergence of so-called entry-level smartphones. Smartphones are mobile devices with operating systems that can run downloaded applications and allow users to access the Internet and social media conveniently from the palm of their hands. This method of

accessing social media is already used by 28% of South Africans, according to Ornico *et al.* (2017). Currently, a variety of smartphones can be bought for under R1000, with some even priced under R600 (Steyn, 2017). Correspondingly, according to a report by the market research company, Growth from Knowledge (GfK) (2018), sales of smartphones in South Africa have increased by 12.4% year-on-year in the first quarter of 2018, while the value of this market segment grew by 22.8% due to a rise in sales of entry-level devices to low- and middle-income consumers (GfK, 2018).

The increased availability of smartphones makes it easier to access news media. To this end, Mitchell, Simmons, Matsa and Silver (2018) conducted a survey of 38 countries to determine the news media habits of citizens. This study used country-specific examples of social media to obtain information regarding how the public prefers to access news media (Mitchell *et al.*, 2018). The social media platforms considered for South Africa were Twitter, Facebook, Pinterest, and Instagram (Mitchell *et al.*, 2018:42). They found that 86% of South Africans follow news about their country, while 31% use social media to obtain news, and 23% prefer to use news websites via the Internet (Mitchell *et al.*, 2018). Their study further showed that 65% of South Africans feel that the news media is doing very well or somewhat well at reporting the news (Mitchell *et al.*, 2018). Furthermore, 63% feel that it is never acceptable when news agencies favour a particular political party over others when reporting the news, while 23% feel that it is sometimes acceptable and 10% expressed no opinion (Mitchell *et al.*, 2018). In terms of fairness, the study found that 30% of South Africans feel that news agencies are not doing well at fairly reporting on different sides of political issues (Mitchell *et al.*, 2018). Table 3.1 provides more detailed demographic information regarding how South Africans utilise social media and the Internet to access news media.

**Table 3.1 South African Daily News Media Access Demographics**

		Age			Gender		Education		Income	
Medium	Total	18-29	30-49	50+	Men	Women	Less	More	Lower	Higher
<b>Social Media</b>	31%	44%	30%	11%	31%	29%	19%	47%	21%	41%
<b>Internet</b>	23%	31%	26%	9%	26%	21%	15%	35%	17%	30%

(Source: Mitchell *et al.*, 2018)

Hashtag campaigns, which are especially utilised by the South African youth, frequently outpace traditional newspapers as events develop that are captured on social media and identified by a specific hashtag. In many cases, this has had the effect of news organisations conveying events to audiences by copying the tweets from activists' accounts and publishing it on their websites.



In South Africa, social media has become a useful channel for citizens to partake in politics, particularly due to increased access offered by mobile smartphones. In concurrence with Di Gennaro *et al.* (2006), as seen in Chapter 2 (Section 2.6), this provides marginalised citizens a potential influence on policy-making by allowing them to communicate easily with government institutions. To this extent, social media enables the public to voice their opinions through comments on news articles or the social media pages of government entities or by participating in collective actions against certain policies (for example the hashtag campaigns mentioned above). According to Schechner (2013:4), a new form of freedom of speech is emerging, in a language that consists of various shorthand styles, images, sound, video and hyperlinks.

For the purpose of this study, it is important to specify the degree to which South Africans have access to, and make use of, the Internet and social media to obtain news. But, as the aim is to analyse public sentiment going forward, the feature of two-way communication provided by social media will be the point of focus.

The current section has shown that social media is on the rise in South Africa. According to the World Bank (2018), 54% of the South African population have access to an Internet connection, while initiatives, such as Project Isizwe (2018), are aiding in improving the public's ability to access the Internet through subsidised free Internet zones. As a result, South Africans have increased access to social media, which allows researchers to obtain important information about South Africans' preferences for accessing news media, for instance, Mitchell *et al.* (2018:23) have shown, that 86% of South Africans are interested in news about their own country, 30% of South Africans feel that the news is not always reported fairly, and 31% of South Africans use social media to access news media. The significance of observing how South Africans prefer to access news media and how it relates to social media, links to the aim of this study; namely, to determine if the inclusion of social media in measurements of policy uncertainty could contribute to the accuracy of such measurements.

The following section will look at the use of Twitter in the context of the information provided about the social media habits of South Africans. The advantages and disadvantages of using social media for academic research purposes in South Africa will also be discussed.

### 3.4 Twitter in South Africa

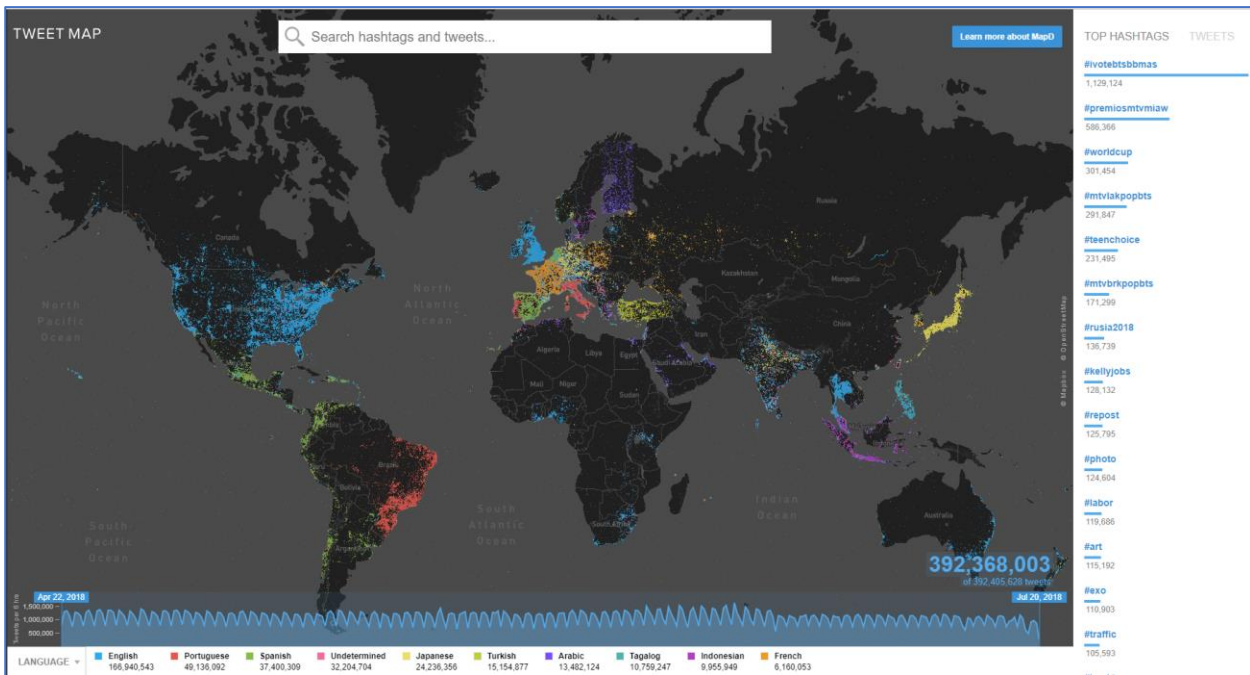
From the previous section, it is evident that the use of social media in South Africa is growing. Every year, more South Africans subscribe to various social media platforms and gain access to the Internet. Internet and social media usage is specifically growing under the age group 18 to 29 (refer to Table 3.1 on page 37) and South Africans have especially become adept at utilising social media to initiate social and political campaigns.

According to Di Gennaro *et al.* (2006) (as discussed in Chapter 2, Section 2.6), the Internet can be a valuable tool to include social groups in the political process who might otherwise have been excluded, such as younger generations who are more engaged in information and communications technology (ICT) (refer to Table 3.1).

Since 32% of South Africans are active users of social media and 31% use social media to access news media, it can be inferred that almost all social media users in South Africa obtain news information through social media platforms. This provides a valuable opportunity to determine public opinion of news about government policies, especially since a key feature of nearly all social media platforms is that they enable users to publish their opinions, either in the form of new statements on their personal social media accounts or in the form of comments on the statements of other users.

Twitter is one such social media platform where users publish statements in the form of short texts. Users can reply to the statements of other users, share the statements of other users, or click on an icon that shows that they approve of a statement. In comparison to other social media platforms, Twitter is especially useful for research purposes. One of the reasons for this is that there are a variety of tools that have been developed especially for Twitter to assist researchers in analysing Twitter data, without having to obtain any prior programming or technical training.

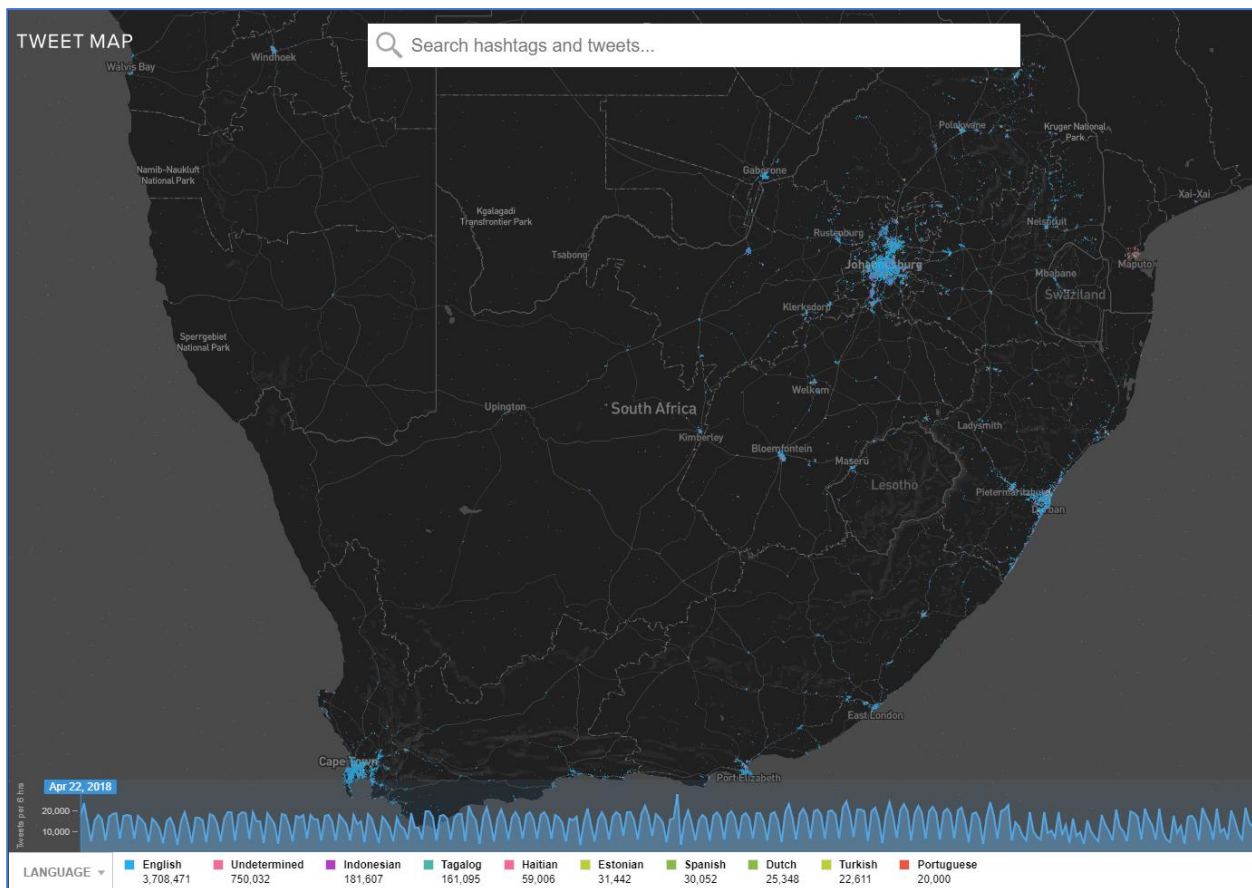
Tweet Map is an example of such an application, which shows the current topics that are trending around the world, as seen in Figure 3.4 below where tweets are illuminated in colours filtered by language. The top discussed topics are listed in the panel on the right by the number of times each featured on Twitter, while a graph at the bottom of the image shows the volume of tweets over a period of approximately three months.



**Figure 3.4 Tweet map world image**

(Source: MapD, 2018)

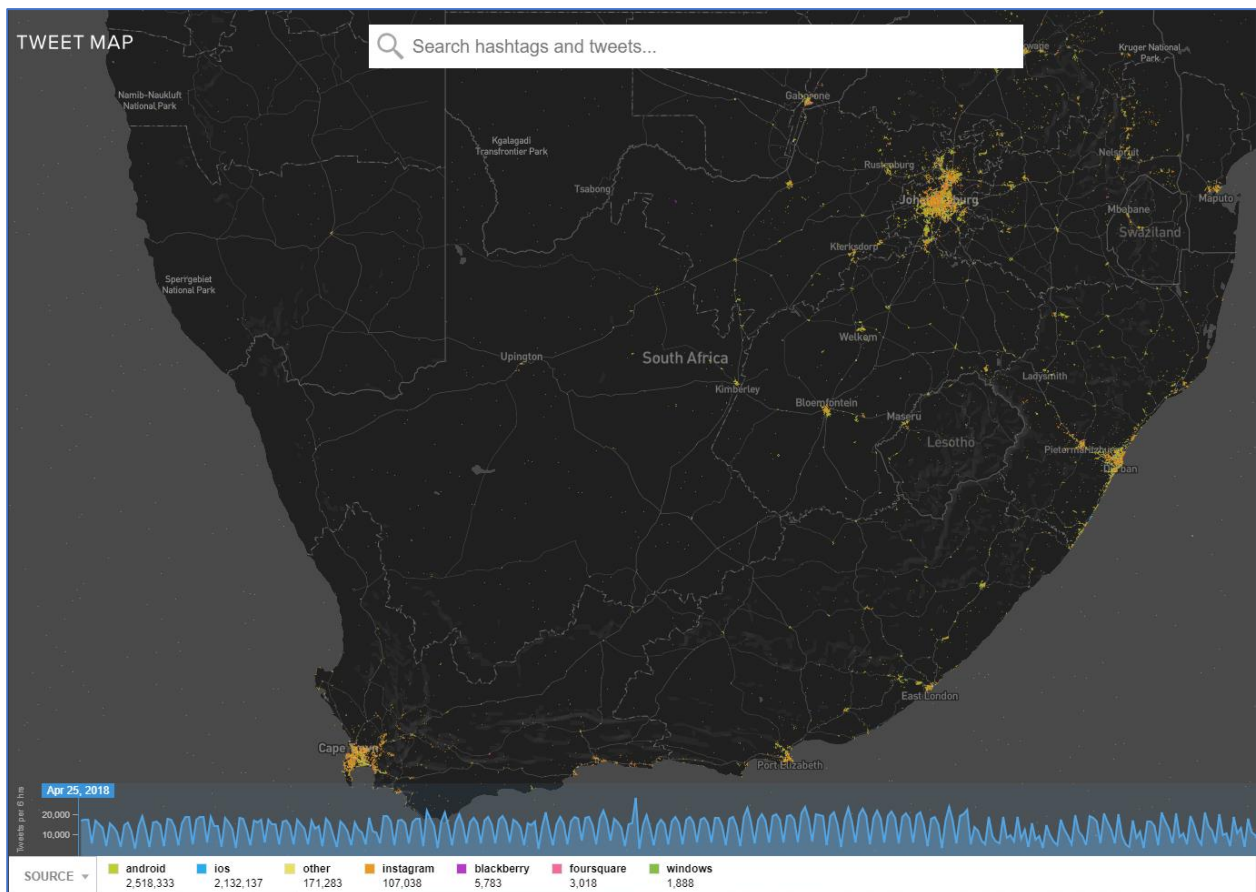
Focussing this map on South Africa, as seen in Figure 3.5 below, shows that the majority of tweets come from large urbanised areas such as Cape Town, Durban, Johannesburg, Bloemfontein, East London, Port Elizabeth, and Polokwane. Figure 3.5 below also shows that English is the language in which most South Africans post on Twitter. There are also a few tweets under the 'undetermined' category which can be assumed to be some of the other South African languages that are not included in Tweet Map's list of languages.



**Figure 3.5 Tweet Map of South African tweet volume by language**

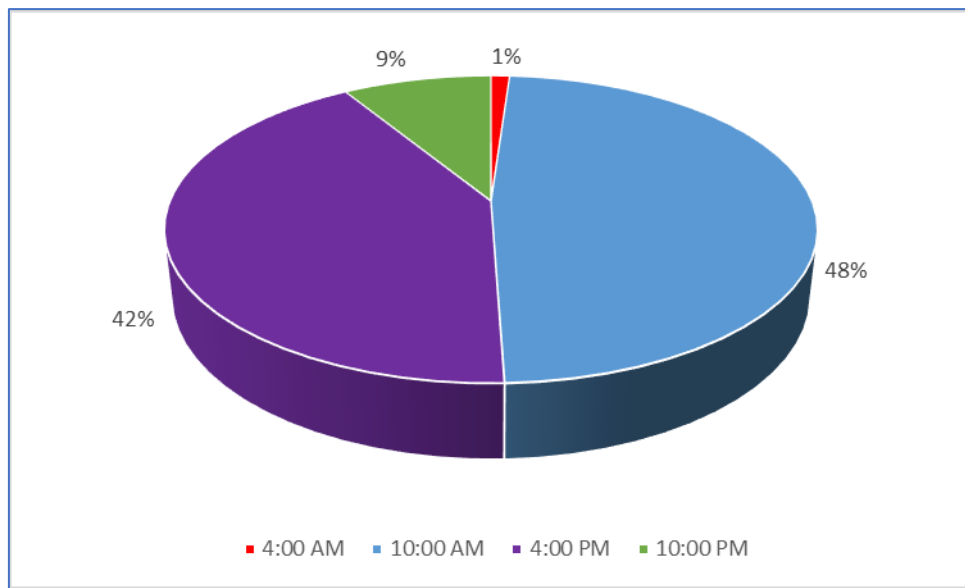
(Source: MapD, 2018)

The application also has an option to filter tweets by source which shows the platform or phone operating system from which a tweet was sent. Since a Twitter account can be linked to an Instagram account, photos and hashtags published on Instagram can be viewed on some users' Twitter accounts as well. From Figure 3.6 below it can be seen that South Africans mostly use the Android and iOS mobile operating systems to publish on Twitter. This corresponds with Section 3.3 which states that most South Africans access the Internet, and by extension social media, via their smartphones. Figure 3.6 also shows that Instagram is a popular platform in South Africa for sharing tweets. While Figure 3.7 – constructed from the tweets per-six-hours graph provided by Tweet Map in Figure 3.6 – shows that the majority of South Africans publish tweets in the morning around 10:00.



**Figure 3.6 Tweet Map of South African tweet volume by source**

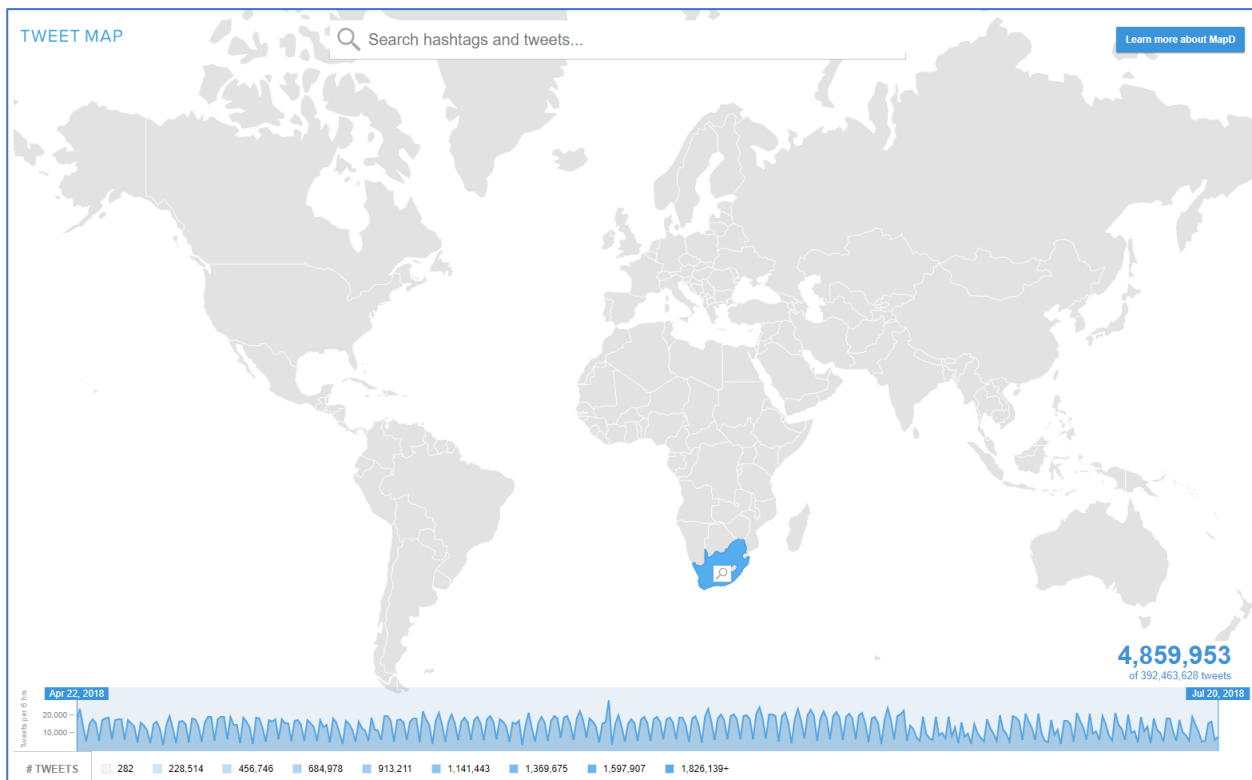
(Source: MapD, 2018)



**Figure 3.7 Distribution of tweet time preference**

(Source: MapD, 2018)

In Figure 3.8 below, Tweet Map's choropleth map function shows that, from a world total of 392 466 628 tweets on trending topics on 20 July 2018 at 21:11, 4 859 953 tweets were made from locations in South Africa. Thus 1.24% of all tweets in the world, at that time, came from South Africa.

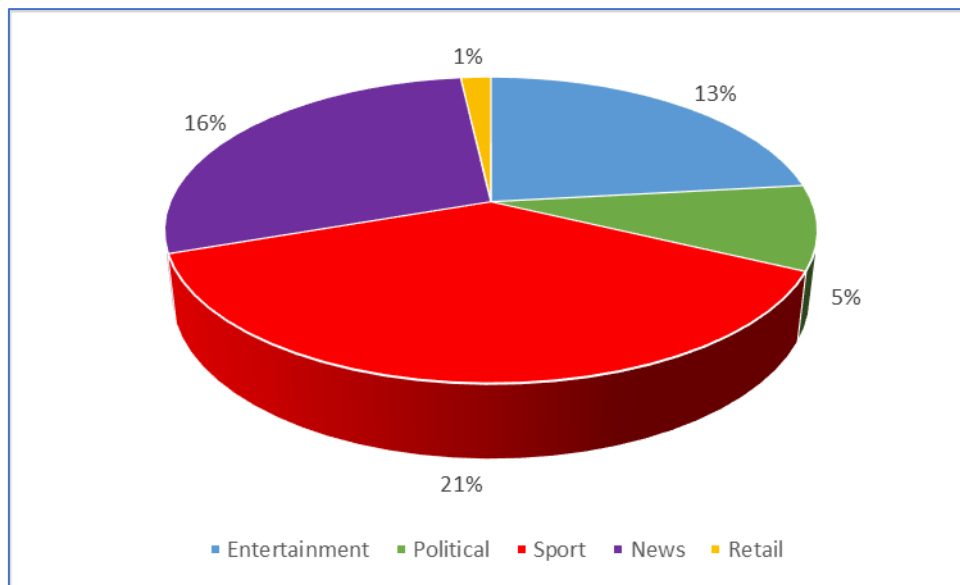


**Figure 3.8 Tweet Map of South African choropleth view**

(Source: MapD, 2018)

According to Socialbakers (2018), the political Twitter profiles with the most followers in South Africa are that of Julius Malema with about 2 million followers, Helen Zille with over 1.3 million followers, and Mmusi Maimane with more than 980 000 followers. The website also provides information on the fastest growing profiles in politics, showing that President Cyril Ramaphosa's profile has gained the most followers (more than 19 900) within one month, while, within the same period, the Economic Freedom Fighters' profile has gained more than 15 000 followers, and Mmusi Maimane's profile has gained more than 14 000 followers (Socialbakers, 2018).

Another useful Twitter tool, Trends 24, provides hourly data of the top discussed topics on Twitter during a 24-hour period. The information obtained from this website was used to construct Figure 3.9 below which shows that the top most discussed topics in South Africa during an average day are sport, news, and entertainment.



**Figure 3.9 South African tweets by topic**

(Source: Trends24, 2018)

Although Twitter is not the most popular social media platform, it is the most useful for research purposes in comparison to other platforms, as it has the least restrictions for accessing information.

In addition to the advantages of using social media as a tool in academic research, discussed in Chapter 2 (Section 2.6), the following section supplements the discussion by highlighting the advantages and disadvantages of using Twitter for academic research from a South African viewpoint.

### 3.4.1 Advantages

Although South Africans prefer Facebook as their social media platform of choice, Twitter is the most accessible application for the purposes of research as text data, at the time of data collection, was limited to 140 characters. The website also does not have a login requirement to be able to view tweets. Through Twitter's 'advanced search' function, access can be gained to all messages related to certain keywords, hashtags, users, and places without the researcher having to create, or log into, a personal Twitter account. Additionally, the hashtag function allows easy grouping of discussions on similar topics, enabling researchers to find and follow conversations with ease (Ahmed, 2015a).

The multiple tools and applications designed to analyse Twitter content (for example Tweet Map, as demonstrated in the previous section) provide valuable time-saving contributions from which insights can be obtained prior to data handling, enabling the researcher to focus on interpretation. In



comparison to traditional data gathering methods, Twitter also provides a much larger pool of information that is easier and simpler to access than traditional surveys. In comparison to surveys, Twitter also does not pose the risk of interviewer bias since data can be obtained as events occur (Ahmed, Bath, & Demartini, 2017:20). The possibility of obtaining real-time data from Twitter allows the researcher to analyse news stories, political events, and crises almost as soon as they happen (Merchant, Elmer. & Lurie, 2011:290). This makes it especially useful in the observation of time series data.

Furthermore, although Twitter is not the social platform with the largest follower base in South Africa, the possible sample size of 8 million South African Twitter users is much larger than that of most traditional data sources. In comparison to traditional measures of policy uncertainty, Twitter also provides an additional benefit of two-way communication. It is this ability of directly observing public opinion that produces the question: Can Twitter serve to enhance the accuracy of existing policy uncertainty measures?

It is also possible that the news-factor of policy uncertainty measures could be featured directly in the observed Twitter content, since most social media users obtain and share information from news media in this manner.

### *3.4.2 Disadvantages*

Although the size of the available data pool is one of the advantages of Twitter, in terms of ethics, it can prove difficult to obtain the written consent of such a large number of participants if the research contains surveys, features specific user publications, or discloses user identities (Ahmed, 2015b).

Another possible drawback is that, as seen in Section 3.3, not all South Africans use Twitter. Some are deterred by a lack of infrastructure, such as the inability to access the internet or to afford a device from which Twitter can be accessed. Some may also prefer to use other social media platforms (for example Facebook or Instagram). Additionally, some South Africans who are using Twitter may not be active users and therefore do not voice their opinions on the platform, although they could be influenced by the publications of other users. This means that some relevant data may be excluded.

Furthermore, the language used to retrieve Twitter data may limit the results. For example, if the keyword 'economic' is searched, it will only render results of tweets that are in English. This will reduce the size of the data sample. The obstacle of language is further magnified by the fact that a new texting language has emerged, due to the limited amount of characters allowed, which does not

adhere to conventional spelling rules (Patil & Atique, 2017:42). Opinion mining tools need to be adapted to be able to interpret this 'incorrect' language.

Biased samples could also be obtained by excluding significant keyword- or hashtag searches to retrieve data, in this case some discussions relevant to the topic researched may be excluded, leading to a systematic bias (Ahmed, 2015b). Conversely, there is also the risk of including irrelevant data such as marketing messages or content from fictitious accounts (Ahmed, 2015b). Additionally, since the use of Twitter as a source of academic data is relatively new, there may be methodological issues regarding its use that is not yet known (Ahmed, 2015b).

Finally, when using automated analysis tools to study social media for sentiment analysis, it is possible that some context could be lost as these tools may not be able to correctly interpret sarcasm or ironic expressions (Aggarwal & Aggarwal, 2017:224).

These potential drawbacks were addressed in various ways, as will be discussed in Chapter 4 (Section 4.2.1).

The following section will provide a concluding summary to Chapter 3.

### **3.5 Conclusion**

This chapter has discussed the impact of policy uncertainty on unemployment, economic growth in South Africa, and research and development expenditure by the private sector. Through these channels, it can be seen that policy uncertainty is a major source of concern to the South African economy.

An overview of the use of social media in South Africa was provided from which it is evident that social media usage is growing among South Africans, especially with regards to political activism. Through the use of the Twitter application, Tweet Map, it was shown that the majority of tweets come from highly urbanised areas and that South Africans prefer to use the Android and iOS mobile operating systems. Other Twitter habits of South Africans were also revealed, such as that most South Africans publish tweets in the morning around 10:00 and that Instagram is a popular platform where tweets are shared. It was further shown that the South African Twitter profiles with the most followers are that of political leaders. Additionally, the Twitter application, Trends 24, was used to show that sport, news, and entertainment are the most popular topics of discussion on Twitter in South Africa.

Finally, the advantages and disadvantages of using social media, and specifically Twitter, as a source of data for academic research were considered. The major advantages include the ease of access, the size of the available data base, the utility of the hashtag function, the multitude of supportive applications developed specifically to obtain information from Twitter, the benefit of real-time data, and the emergence of new methods of conducting and interpreting sentiment analysis. The obstacles, on the other hand, consist of possible ethical difficulties, the fact that not all South Africans use Twitter, language limitations, the possibility of excluding relevant keywords or of unintentionally including irrelevant content, unexpected methodological issues, and the possibility of losing context when using automated analysis tools.

Chapter 4 presents the methodology followed, the analysis of the data, and the results obtained. The possible difficulties, as discussed in Section 3.4.2 will also be addressed, under the description of the data used. The specific objectives of this study, stated in Chapter 1 (Section 1.3.2) will also be addressed.

## CHAPTER 4

# EMPIRICS: DESCRIPTION OF THE METHOD, DATA ANALYSIS AND RESULTS

### 4.1 Introduction

Chapter 2 stated the importance of being able to measure policy uncertainty by emphasising the effect that policy uncertainty can have on the economy due to its impact on investment, production, employment, consumption, inflation, stock markets, and exports. Thus, an accurate measure of policy uncertainty will assist policymakers by enabling them to correctly assess the current economic environment and by providing additional information with regards to forecasting and the reception of public policies.

The use of Twitter in academic research has also been discussed in Chapter 2 (Section 2.6) in terms of studies such as that by Brown *et al.* (2018), which showed that Twitter data can aid in the interpretation of news following events. Additionally, data from Twitter is used to predict stock market movements and to determine marketing strategies, while also being utilised in economic forecasting (Barnes, 2014; Bollen *et al.*, 2010; Pagolu *et al.*, 2016; Nisar *et al.*, 2018; Ramli, 2012; Wieczner, 2015).

Chapter 2 provides, firstly, the validation for obtaining an accurate measure of policy uncertainty for South Africa, and secondly, the literature basis of existing studies on which the methods, following in this chapter, will continue.

The motivation for using Twitter as a source of data in the measurement of policy uncertainty in South Africa was also stated in Chapter 3 (Section 3.3), where it was shown that, Twitter is growing in popularity as a platform for engagement in public discourse (Ornico *et al.*, 2017). This is supported by the advantages of using Twitter data for academic research, as stated in Chapter 3 (Section 3.4.1), which include the ease of obtaining data with functionalities such as the 'advanced search' and 'hashtag' functions and applications like Tweet Map. Additionally, data interpretation is improved by tools specifically designed for Twitter, while the platform also provides easy access to a large pool of real-time data which lowers the risk of interviewer bias (Ahmed *et al.*, 2017:20). The fact that Twitter offers users the ability to react to content published by other users also makes it unique as it enables researchers to directly assess public reaction. Based on these advantages, Twitter will be used as the social media platform for data retrieval in this study.

However, Chapter 3 (in Section 3.4.2) also presented the disadvantages of using Twitter as a source of data which include ethical problems in terms of obtaining written consent if the research entails publishing the identities or specific content created by users, the fact that not all people in the data samples actively use or publish on Twitter, limitations due to the language used to obtain data, exclusions of relevant keywords when obtaining data, the inclusion of irrelevant data, methodological issues not yet identified due to the novelty of using Twitter as a source of data, and the possibility of losing context when using automatic analysis tools (Ahmed, 2015b). In spite of these possible disadvantages, which will be addressed in this chapter, Twitter presents a valuable source of information.

Chapter 4 will firstly, describe the data used in this study, after which an analysis of the data will be provided based on the first and second specific objectives, as stated in Chapter 1 (Section 1.3.2). Following the data analysis, the results obtained will be discussed, while the third specific objective, namely, of providing guidelines to policymakers on how to respond to policy uncertainty, will be addressed in Chapter 5 (Section 5.2.3).

## **4.2 Description of data used**

Data for this study was collected from Twitter and various Internet based news- and data sources. Tweets were obtained from Twitter in a daily frequency but were grouped in monthly data sets for the purposes of analysis. The data used for this study is quantitative time series data observed from 01 June 2010 to 31 December 2016. A location limit was also applied were necessary to obtain data specific to South Africa.

### *4.2.1 Twitter data collection*

According to Steinert-Threlkeld (2018:9), the three simplest methods of acquiring data from Twitter are purchasing the data, making use of Twitter's application programming interface (API), or to collaborate with others who have already collected the required data. However, at the time of data collection, Twitter had disabled access to its API to non-developers. Thus, for the purpose of simplicity and cost-effectiveness, this study pursued the method of data collection described below.

Based on the studies by Baker *et al.* (2016), Hlatshwayo *et al.* (2016), Brogaard *et al.* (2015), Nisar *et al.* (2018) and the NWU (2016), as discussed in Chapter 2, keywords that are likely to reveal sentiment regarding the government's economic policies were identified. These keywords are: 'economy', 'economic', 'policy', 'politics', 'political', 'regulate', 'regulation', 'parliament', 'legislate',

'legislation', 'SARB' and 'government'. Although Twitter was created in March 2006, when the location limitation was applied, results for these search terms were only available from June 2010. These keywords are only applicable to the second method of data analysis, which will be discussed in Section 4.3.3.

Additionally, in accordance with the studies by Baker *et al.* (2016), Bloom *et al.* (2013) and Hlatshwayo *et al.* (2016), all tweets containing the keyword 'uncertain' and 'uncertainty' were also collected. However, tweets containing these keywords were only available from July 2010. The data for these keywords was not searched under the condition of simultaneous appearance with the keywords associated with economic policy mentioned above, as is the case in the study by Hlatshwayo *et al.* (2016). This is attributed to the insufficient availability of tweets containing simultaneous references to all three of the word categories mentioned in these studies, namely, 'economic', 'policy' and 'uncertainty'. A possible reason for the lack of such tweets could be that with consideration of the location limit, the data pool is somewhat constricted. Additionally, with Twitter's limitation on the amount of characters allowed per statement, Twitter users may be less likely to use a variety of large words that fill their limited character space. Thus, one of the disadvantages of using social media for data collection, as discussed in Chapter 3 (Section 3.4.2), was encountered, which is that users possibly revert to using language that does not adhere to conventional spelling rules.

Although the tweets containing the keywords 'uncertain' and 'uncertainty' are not guaranteed to also contain references to 'economic' or 'policy', it is hypothesised that general uncertainty will increase when people feel uncertain about economic policies. This is also linked to the study by Gil de Zúñiga *et al.* (2014), discussed in Chapter 2 (Section 2.6), which theorised that a 'political self' may be revealed by conversations that are not explicitly political. These keywords were used in both the first and second methods of data analysis, as will be discussed in Sections 4.3.1 and 4.3.3.

The following process was followed to retrieve the data pertaining to the first and second methods of data analysis, which will be discussed in this chapter: The above-mentioned keywords were entered in Twitter's 'advanced search' function in the search box that instructs the search to display tweets containing any of these keywords. In order to collect tweets from all profiles, the 'People' category – which allows searches in specific user profiles – was left clear. To keep the search mainly localised to South Africa, Bloemfontein was chosen as the location for the 'Places' category, as it is the largest city located approximately in the middle of South Africa. The reason it is beneficial to use a location as near as possible to the centre of the country, is that the search in Twitter can be instructed to obtain tweets within a certain radius from the chosen location. To this end, the radius chosen for the search was 570 miles (or almost 917 km) in order to include Cape Town, which is the farthest major city from Bloemfontein, and as many tweets originating within South Africa as possible. Although this may lead to some tweets from neighbouring countries being included in the sample,

most of the content will come from South Africa. Thus, by means of volume, the tweets from South Africa will outrank those inadvertently included from neighbouring countries during the data analysis process.

The Twitter 'advanced search' function also allows inputs of dates for the start and end of the search. For this purpose, tweets were searched from 1 June 2010 to 31 December 2016 on a monthly basis, which provided daily tweets grouped under each month. The time period observed was chosen from the first date of available data until the end of the last year prior to commencement of this study

The text data obtained was then cleaned to remove any content copied from the platform that did not form part of a tweet, which were mainly descriptions of clickable buttons that provide additional options to users, such as 'more' (for more options), 'retweet' (to share a user's tweet), 'reply' (to reply to a tweet), 'like' (to approve of a tweet), and 'direct message' (to send a message directly to the person who created the tweet). This was done to prevent the Linguistic Inquiry and Word Count (LIWC) programme (which will be discussed in Section 4.3.2) from classifying these words under a specific sentiment and providing false results. For this purpose, the date of the tweet and the contributor's name and username were also removed.

With regards to Twitter, the LIWC programme also recommends removing Universal Resource Locator (URL) addresses, hashtags, Twitter handles – usernames that are usually preceded by the '@' sign when one user refers to another – and email addresses (Pennebaker, Booth, Boyd, Jordan & Francis 2015a:16). Since many of the hashtagged terms contain expressions of emotion, only the pound sign (#) was removed to enable LIWC to analyse the words. The collection rendered approximately 12 800 tweets.

Since all usernames and contributor names were removed, one of the disadvantages of using Twitter for research purposes, namely, that of ethical issues, was overcome, as no user was personally identified, or their identities used for any purpose during the course of this study.

In accordance with the studies by the NWU (2016) and Moore (2017), a search was also conducted for tweets from economists of the South African branches of leading financial firms, such as PricewaterhouseCoopers (PwC), Deloitte, Ernst & Young (EY), and KPMG. However, most of these professionals do not have Twitter profiles, or do not actively use their profiles. This could be attributed to the strict social media policies in place at almost all major companies as well as the fact that a misplaced or misinterpreted statement on social media can lead to a damaged reputation and/or dismissal. Thus, due to data unavailability, this measurement was not included.

After concluding the Twitter data collection process, the possible disadvantages of using Twitter as a source of data, described in Chapter 3 (Section 3.4.2), can be addressed as follows: The fact that not all South Africans use Twitter or are active users, would have been an issue even when using other forms of social media and cannot be remedied by the researcher. Consequently, this possible obstacle is neutralised and it is assumed that Twitter will provide a feasible sample to reach the objectives set out at the start of this study. The limitations due to language could lead to the exclusion of relevant data; however, according to Figure 3.5 in Chapter 3 (Section 3.4) the majority of South Africans make statements on Twitter in English, which is also the language used for the keyword search. While it is possible that certain relevant content in other languages will still be excluded, this study will use the statements made in English as a sample representative of the whole. Furthermore, this study has taken all possible steps to lower the probability of excluding a relevant keyword, by obtaining the most significant keywords as identified by previous research, discussed in Chapter 2. While it is possible that irrelevant content could be included, it has been assumed that the volume of relevant content will outrank any false data inadvertently included. The removal of URL's and email addresses also aids in limiting the amount of irrelevant and/or marketing data that were included in the sample. Lastly, the problem of unidentified methodical issues can only be solved by conducting studies, such as this one, which could lead to the identification of such problems, and as they are currently unidentified, there is no realistic method of preventing them from occurring.

The following section describes the collection of data from other sources used in comparison to the Twitter data to evaluate its usefulness as a measurement of policy uncertainty.

#### *4.2.2 Data collection from other sources*

Based on the availability of data, the following measures of uncertainty, as discussed in Chapter 2 (Section 2.5), were compared to the data collected from Twitter to determine its viability as a measure of policy uncertainty: news data, interest rates, stock market price fluctuations, household expenditure, investment, employment, political events, and inflation. GDP data and the existing South African policy uncertainty index (developed by the NWU) were used as benchmark tests.



In accordance with the statement by Bosch (2017:230) that data from social media should be viewed alongside traditional media sources, data from news organisations was obtained as follows: The same keywords that were used for the collection of Twitter data regarding government economic policies were used to search for South African based news articles. To conduct the search, the following was entered into the Google search box: 'Economy OR economic OR policy OR politics OR political OR regulate OR regulation OR parliament OR legislate OR legislation OR SARB OR government in South Africa'. The keywords were searched based on a monthly frequency within the time period of 01 June 2010 to 31 December 2016 and the search was limited to news results. The search results were sorted by relevance and the first 30 articles rendered by the search were copied to a text document. All pictures and URL- and email addresses were removed in accordance with the LIWC programme's recommendations, stated in Section 4.2.1.

Additional data was obtained for the period of 01 June 2010 to 31 December 2016 from a variety of sources. Daily prices of the FTSE/JSE All Share Index (JALSH) were obtained from Investing.com and monthly short-term interest rates from the webpage of the OECD. Quarterly gross capital formation data – as a proxy for investment – was also obtained from the OECD's webpage, although this data set was only available from 2011. Quarterly data for private consumption expenditure – available from the fourth quarter of 2011 – was acquired from the webpage of the SARB. While inflation data, in the form of the monthly Consumer Price Index (CPI) inflation rate, as well as quarterly employment data, was obtained from StatsSA. As discussed, monthly news data were acquired from various news webpages, while political events were also obtained daily from news webpages. Quarterly GDP data (by expenditure in constant prices) was acquired from the webpage of the economic research department of the Federal Reserve Bank of St. Louis. Although, according to Asteriou and Hall (2011:325), it is standard practice to use GDP per capita as an indicator for economic growth, data for this indicator was only available on an annual basis, providing too few observations for the period studied in this paper. Data from the existing policy uncertainty index – developed by the NWU – was obtained from quarterly published work by the School of Business and Governance at the NWU.

During the data collection phase, data was collected based on a monthly frequency. However, in certain cases, as mentioned above, monthly data was unavailable and was substituted by quarterly data.

The following section explains the data analysis process by discussing the word processing programme used to quantify text data and the methods employed to meet the objectives set in Chapter 1 (Section 1.3).

### 4.3 Data analysis

The data analysis phase consists of two methods, which will be discussed in the following sub-sections. The aim of these methods is to determine if a Twitter-based measure of policy uncertainty corresponds with existing measures of policy uncertainty and to test its ability to provide information regarding policy uncertainty.

#### 4.3.1 Method 1

The first method serves as a foundation to the second method and makes use of daily Twitter data, as well as daily data relating to political events. Since the data for political events is not applicable to method two, the first method also covers the comparison of the Twitter policy uncertainty measurement to this indicator, as discussed in Chapter 2 (Section 2.5) and Section 4.2 of the current chapter.

The first method consists of a test to determine if Twitter can provide meaningful data on policy uncertainty. Based on the work by Baker *et al.* (2016), Bloom *et al.* (2013) and Hlatshwayo *et al.* (2016) – as examined in Chapter 2 (Section 2.5) – this method made use of the keywords ‘uncertain’ and ‘uncertainty’ collected during the process followed as discussed in Section 4.2.1. For this test, the data was only observed for the period of 01 July 2010 to 31 December 2011, since this method involves graphically demonstrating the results on a daily basis and a longer time frame would have produced difficulties with regards to presentation. The daily occurrence of the word ‘uncertain’ in the text files was then counted, using the COUNTIF function in Excel. The function counts a variable if it includes the base word, which is ‘uncertain’, ruling out the need to do a separate count of the word ‘uncertainty’.

In the next step, based on studies by Bollen *et al.*, (2010:4, 2011:453) discussed in Chapter 2 (Section 2.6), the data obtained from the above exercise was plotted on daily graphs, showing data in increments of six months at a time, along with the occurrence of significant political events in South Africa. As the daily frequency of the use of any of the keywords rarely varied above three, a value of three was appointed to a political event in order to distinctly indicate a spike on the graph, providing a clear reading of possible trends. The resulting graphs are shown in Annexure A, Figures A1 to A3. From these graphs, it can be seen that spikes in uncertainty tend to occur around political events. Although this test is a rudimentary experiment, it provides the basis for the ensuing study and further assessments. It also responds to the first part of the first specific objective stated in Chapter 1 (Section 1.3.2), by providing an evaluation of Twitter data trends against significant political events.

Before discussing the second method used in this study, it would be meaningful to explain how the Linguistic Inquiry and Word Count (LIWC) programme functions, as it was used to quantify the qualitative data obtained from Twitter and news media. This overview, provided in the following section, will serve to clarify the results obtained from the second method, presented later in this chapter.

#### *4.3.2 The LIWC programme*

LIWC is a word processing programme designed to analyse a given text by calculating the proportion of words reflecting various emotions, mind-sets, speech, and social concerns (LIWC, 2018). The programme's language categories were developed with the specific aim of capturing the psychological and social states of text writers (LIWC, 2018). In addition to a text analysis unit, LIWC consists of various dictionaries from which a user can choose (LIWC, 2018). When a document is analysed, the programme compares each word in the given text to the user specified dictionary which then arranges the word into the relevant psychological category (LIWC, 2018). The results are provided as a portion of the total words matching each category in the dictionary (LIWC, 2018). The programme consists of three internal dictionaries, namely the LIWC2015 dictionary and two previous versions of this dictionary titled LIWC2001 and LIWC2007 (LIWC, 2018). For the purpose of this study, the main dictionary used is the LIWC2015 dictionary as it includes updated words and expressions specific to social media speech. It consists of approximately 6 400 words which also include a number of emoticons (Pennebaker, Boyd, Jordan and Blackburn, 2015b:2). Emoticons are short for emotion icons and are representations of facial expressions that are formed with the use of a variety of keyboard characters (English Oxford Living Dictionaries, 2018c).

The programme defines one or more categories, called sub-dictionaries, for each word included in the main dictionary, for example 'Sadness', 'Overall Affect', 'Negative', 'Verb', 'Emotion', and 'Past Focus' in relation to the dictionary word 'cried' (LIWC, 2018). It should be noted that the word categories are hierarchically arranged, meaning that LIWC will classify all words that are included in the 'Sadness' category as words pertaining to a negative emotion, which also provides the possible 'Overall Affect' of the statement (LIWC, 2018).

LIWC contains a separate dictionary for each of the emotion dimensions defined in the programme (LIWC, 2018). When these words are used, they are classified under the relevant category to provide an end result in the form of a percentage of words relating to a specific emotion (LIWC, 2018). The developers of LIWC constructed the emotion-specific dictionaries by asking several human judges to collect all the words that are associated with a specific emotion from reliable dictionaries and thesauruses (LIWC, 2018). After the creation of a master list for each emotional category, each word was evaluated by a group of judges to determine if that word truly belongs to the specific category (LIWC, 2018).

One of the possible drawbacks of the programme, in line with the discussion provided in Chapter 3 (Section 3.4.2), is that some context could be lost, as the programme does not evaluate whole sentences, but instead evaluates words individually to determine the relevant category. This could lead to certain words being misclassified, such as the word 'mad' which is generally used to portray anger, but can also be used to portray certain positive emotions for example: 'She is mad about running'. Here, the word mad will be incorrectly classified under the 'anger' and 'negative' categories. However, the programme's information webpage states that in such cases, if the feeling really is positive instead of angry, a person will use additional positive words in the text that will result in the overall mood being classified as positive (LIWC, 2018). To this extent, the programme is also not able to identify sarcasm, metaphor, and irony, but ought to be able to correctly classify the overall emotion based on other word choices (LIWC, 2018). Thus, these classification errors should not have a major impact on the results as they are offset by the way in which words are normally used (LIWC, 2018).

Due to the possibility of the above-mentioned classification errors, the accuracy of the results obtained from LIWC increases with a document's word count (LIWC, 2018). The programme's disclaimer warns against analysing text files containing fewer than 50 words (LIWC, 2018). In terms of this criteria, LIWC is suitable for use in this study as the text file containing the least amount of words in terms of the Twitter data contains 579 words, while the text file containing the least amount of words relating to the news data contains 6 310 words.

When a text document has been analysed, LIWC provides numerous results of which only those applicable to this study will be discussed. The main LIWC output variables, relating to Twitter, that were used include:

- Anx: This variable reflects the extent to which the writer feels anxious, worried or fearful (Pennebaker *et al.*, 2015b:13) and
- Certain: This variable indicates the conviction of speech, where a lower number is indicative of uncertain or insecure feelings (Tausczik & Pennebaker, 2010:41).

In terms of the news data, the LIWC output variable used to compare to the Twitter data is the Negemo variable. This variable indicates the percentage of words relating to negative emotions (Pennebaker *et al.*, 2015b:13).

Tausczik *et al.* (2010:37) state that the words used in normal daily routines reflect a person's thoughts, the subjects of their attention, their feelings, things that they find pleasant and unpleasant, and the way that they analyse and organise the world around them. This statement provides a summary of the motif of this study for using LIWC's ability to analyse text and to provide numerical results relating to the emotional states of Twitter users.

From this section, it can be seen that the LIWC programme is a useful tool for quantifying qualitative data. Although Twitter's character limit of 140 (at the time of data collection) leads to the use of language that is considerably different from formal text, with tweets often containing misspellings and a vocabulary unique to short internet-based texts (netspeak), Sylwester and Purver (2015:4) found that the programme's accuracy regarding Twitter data compares well to other methods of sentiment analysis. Furthermore, according to Pennebaker *et al.* (2015a:16), LIWC's dictionary does capture the majority of netspeak words (for example 'lol' or '4ever') used in shorthand communications, which makes it suitable for application to Twitter text.

The following section explains the second method in which the LIWC programme is utilised to analyse text from Twitter and news articles, to provide quantitative results that are comparable to the data discussed in Section 4.2.2. This will be done in keeping with the first specific objective, stated in Chapter 1 (Section 1.3.2).

#### 4.3.3 Method 2

In Section 4.3.1, it was shown that the frequency with which the words 'uncertain' and 'uncertainty' are used on Twitter corresponds with the occurrence of major political events. While Section 4.3.2 explained how the LIWC programme functions.

Whilst a part of the first specific objective, stated in Chapter 1 (Section 1.3.2), was answered in Section 4.3.1, this section will deal with the remainder of the first objective. Thus, the second method entails comparing the data obtained from Twitter to various other measures of policy uncertainty, as identified in Chapter 2 (Section 2.5). The data acquired from Twitter will henceforth represent the Twitter measurement of policy uncertainty. Once the comparison has been made to the selected existing policy uncertainty measures (as identified in Section 4.2.2) the Twitter measures of uncertainty will also be compared to two benchmarks of uncertainty, namely economic growth and the existing South African policy uncertainty index developed by the NWU.

During the first step the data from Twitter and various news sources – acquired and processed as discussed in Sections 4.2.1 and 4.2.2 – were analysed by the LIWC programme. This process provided monthly results regarding ‘Certain’, ‘Anx’ and ‘Negemo’, as explained in Section 4.3.2. These results, along with the data relating to other measures of policy uncertainty, identified in Section 4.2.2, were analysed with the help of the computer-based econometric programme EViews 9. Based on the studies by Aizenman *et al.* (1991), Arbatli *et al.* (2017), Bollen *et al.* (2010, 2011), Pagolu *et al.* (2016), Nisar *et al.* (2018), and Ozturk *et al.* (2018), discussed in Chapter 2, the correlations between the Twitter uncertainty measurements and various alternate uncertainty measures were calculated. For the purpose of this study, Pearson’s correlation was the main method utilised to determine the level of association between the Twitter measures of uncertainty and alternative uncertainty indicators.

In line with Gujarati’s (2003:23) definition of correlation analysis, this study is concerned with measuring the degree and strength of association between variables. Correlation is given by the symbol  $r$  and if it is determined that there is a correlation between variables, it serves as an indication that a change in one variable is statistically associated with a change in another variable (Burnham, 2015). The value of  $r$  can vary between minus 1 and positive 1, where a value of minus 1 is indicative of a perfect negative linear relationship and a value of positive 1 shows a perfect positive linear relationship, while the closer the  $r$  value is to zero, the weaker the correlation (Nisar *et al.*, 2018:108). The absolute value of  $r$  indicates the strength of the linear relationship between variables (Nisar *et al.*, 2018:108). In this study, a probability value ( $p$ ) of less than 5% is accepted as a statistically significant relationship and it is assumed that the variables are linearly related.

A major drawback of the correlation method is that the ability to draw multiple conclusions from the  $r$  value is limited as it does not take into account the possible impact of alternate independent variables (Nisar *et al.*, 2018:109). Furthermore, as stated by Gujarati (2003:22-23), causation cannot logically merely be proven by a statistical relationship, but must also be based on theoretical considerations. However, the aim of this study is to determine if the Twitter uncertainty measurement is comparative to current measures of policy uncertainty and can thus serve as an additional source

of information regarding policy uncertainty. To this extent, and by basing the preliminary hypotheses on the theoretical framework outlined in Chapter 2, the correlation method was deemed suitable to reach the objectives outlined in Chapter 1 (Section 1.3). Expectations regarding the direction of association between Twitter sentiment and the comparative indicators are based on the literature reviewed in Chapter 2 and are stated prior to the presentation of each estimation output.

For all calculations, the hypotheses are broadly set as follows:

Null hypothesis: There are no statistically significant relationships between Twitter sentiment and the various comparative indicators.

Alternative hypothesis: There are statistically significant correlations between Twitter sentiment and the comparative indicators.

In the first set of calculations, the correlation coefficients are calculated for the datasets available in monthly frequencies, consisting of 80 data observations ( $n = 80$ ) and five variables. Starting with the correlation coefficients relating to the 'Anx' variable obtained from the LIWC programme for Twitter that are analysed, as shown in Table 4.1, in accordance with the following theoretical expectations:

- Twitter Anxiety: The LIWC output indicating the anxiety calculated from the Twitter data, as discussed in Section 4.3.2.
- Negative Emotions In News: The LIWC output relating to negative emotions from news sources is expected to have a positive correlation with Twitter Anxiety.
- Short-Term Interest Rates: This is the data set for short-term interest rates. Due to the disparity in views regarding the relationship between uncertainty and interest rates, as discussed in Chapter 2 (Section 2.3), this study forms no prior expectation of the relationship between Twitter Anxiety and short-term interest rates (OECD, 2018d).
- CPI inflation rate: The Consumer Price Index inflation rate is expected to have a positive correlation with Twitter Anxiety as an increase in negative sentiment is associated with higher inflation (StatsSA, 2018b).
- FTSE/JSE ALSI: Daily prices of the FTSE/JSE All Share Index (JALSH) is expected to have a negative correlation with Twitter Anxiety under the assumption that higher uncertainty leads to a decline in prices of South African listed stocks.

Table 4.1 shows that, as expected, Twitter Anxiety is positively correlated with Negative Emotions In News and although the relationship is weak, it is statistically significant, causing the null hypothesis to be rejected. Twitter Anxiety is positively correlated with Short-Term Interest Rates. However, the relationship is very weak and statistically insignificant, indicating that the null hypothesis cannot be rejected. In line with expectations, Twitter Anxiety is positively correlated with CPI, although this

relationship is also weak and not statistically significant. Thus, the null hypothesis cannot be rejected. Finally, the null hypothesis is also not rejected with regards to Twitter Anxiety and FTSE/JSE ALSI as the correlation coefficient is, contrary to expectations, positive, relatively weak and statistically insignificant.

**Table 4.1 Results: Correlation coefficients for Twitter Anxiety, Negative Emotions In News, Short-Term Interest Rates, CPI and FTSE/JSE ALSI**

Correlation	Twitter Anxiety
Probability	
Twitter Anxiety	1,000
	–
Negative Emotions In News	0,296
	(0,008)
Short-Term Interest Rates	0,068
	(0,549)
CPI	0,069
	(0,547)
FTSE/JSE ALSI	0,140
	(0,220)

(Source: Author's estimated output)

The second calculation provides the correlation coefficients for the Twitter data 'Certain' output from LIWC. This variable was renamed 'Twitter Conviction' to avoid confusion with the variable named 'Twitter Uncertainty'. The results are analysed according to the following expectations:

- Twitter Conviction: The LIWC variable indicating the degree of conviction with which statements are made, as calculated from the Twitter data (discussed in Section 4.3.2).
- Negative Emotions In News: Is expected to have a negative correlation with Twitter Conviction.
- Short-Term Interest Rates: Again, no prior expectation of the relationship between Twitter Conviction and short-term interest rates is formed.
- CPI inflation rate: Is expected to have a negative correlation with Twitter Conviction as an increase in positive sentiment is associated with lower inflation.
- FTSE/JSE ALSI: Is expected to have a positive correlation with Twitter Conviction under the assumption that an increase in conviction is associated with an overall increase in prices of South African listed stocks.



The results shown in Table 4.2 oppose the expectation of a negative relationship between Twitter Conviction and Negative Emotions In News, as the relationship is relatively weak but statistically significant, indicating that the null hypothesis can be rejected. Twitter Conviction and Short-Term Interest Rates are positively related and, while the relationship is somewhat weak, it is statistically significant which leads to the rejection of the null hypothesis in favour of the alternative hypothesis. The correlation between Twitter Conviction and CPI is weak and positive, contrary to expectations, but statistically insignificant which indicates that the null hypothesis cannot be rejected. Twitter Conviction is positively correlated with FTSE/JSE ALSI, as expected. The relationship is relatively strong and statistically significant which leads to the rejection of the null hypothesis in favour of the alternative hypothesis.

**Table 4.2 Results: Correlation coefficients for Twitter Conviction, Negative Emotions In News, Short-Term Interest Rates, CPI and FTSE/JSE ALSI**

Correlation	Twitter Conviction
Probability	
Twitter Conviction	1,000
	–
Negative Emotions In News	0,277
	(0,013)
Short-Term Interest Rates	0,239
	(0,034)
CPI	0,126
	(0,269)
FTSE/JSE ALSI	0,526
	(0,000)

(Source: Author's estimated output)

The final correlation coefficient calculations for monthly data entailed determining the degree of association between the average monthly use of the words 'uncertain' or 'uncertainty' from Twitter and the identified indicators of uncertainty. The results are shown in Table 4.3 and analysed according to the following expectations:

- Twitter Uncertainty: The average monthly use of the words 'uncertain' and 'uncertainty' obtained from Twitter, as discussed in Section 4.2.1.
- Negative Emotions In News: Is expected to have a positive correlation with Twitter Uncertainty.

- Short-Term Interest Rates: As stated, no prior expectation is formed regarding the correlation between Twitter Uncertainty and short-term interest rates.
- CPI inflation rate: Is expected to have a positive correlation with Twitter Uncertainty as an increase in negative sentiment is associated with higher inflation.
- FTSE/JSE ALSI: Is expected to have a negative correlation with Twitter Uncertainty under the assumption that an increase in uncertainty is associated with a decline in prices of South African listed stocks.

The results support the expectation of a positive association between Twitter Uncertainty and Negative Emotions In News, although the relationship is weak and not statistically significant. Thus, the null hypothesis cannot be rejected. The correlation between Twitter Uncertainty and Short-Term Interest Rates is negative, but this relationship is also weak and not statistically significant, indicating that the null hypothesis cannot be rejected. Twitter Uncertainty and CPI is positively correlated, in line with expectations, and although the relationship is relatively weak, it is statistically significant which leads to the rejection of the null hypothesis. In contrast to expectation, Twitter Uncertainty is positively correlated with FTSE/JSE ALSI. However, the relationship is weak and statistically insignificant, showing that the null hypothesis cannot be rejected.

**Table 4.3 Results: Correlation coefficients for Twitter Uncertainty, Negative Emotions In News, Short-Term Interest Rates, CPI and FTSE/JSE ALSI**

Correlation	Twitter Uncertainty
Probability	
Twitter Uncertainty	1,000
	–
Negative Emotions In News	0,018
	(0,877)
Short-Term Interest Rates	-0,203
	(0,076)
CPI	0,324
	(0,004)
FTSE/JSE ALSI	0,145
	(0,209)

(Source: Author's estimated output)

The ensuing correlation coefficients will be calculated in terms of the data obtained in quarterly frequencies (as discussed in Section 4.2.2). Due to data availability, the benchmark comparisons

will only be done in terms of the quarterly data. For this purpose, frequency conversions were performed on the monthly Twitter data in EViews to convert the data to quarterly frequencies.

The correlation coefficients were first calculated in terms of the Twitter Anxiety variable with the following expectations:

- Twitter Anxiety: The LIWC output indicating anxiety, calculated from the Twitter data, as discussed in Section 4.3.2.
- Employment: Is expected to have a negative correlation with Twitter Anxiety as potential employers become averse to accumulating expenses in an uncertain economic environment.
- Gross Capital Formation: Gross capital formation is expected to have a negative correlation with Twitter Anxiety under the assumption that an increase in negative sentiment is associated with a decline in the willingness of businesses to expand their capital outlays.
- Household Consumption Expenditure: Final consumption expenditure by households is expected to have a negative correlation with Twitter Anxiety as an increase in negative sentiment is associated with higher precautionary saving and thus lower consumption expenditure.

From Table 4.4, it can be seen that the expectations of a negative relationships between Twitter Anxiety and all three variables are not supported. The correlation coefficient for Employment is relatively weak and statistically insignificant, indicating that the null hypothesis cannot be rejected. Gross Capital Formation and Household Consumption Expenditure, show moderate relationships with Twitter Anxiety that are statistically significant, indicating that the null hypothesis is rejected in both cases.

**Table 4.4 Results: Correlation coefficients for Twitter Anxiety, Employment, Gross Capital Formation and Household Consumption Expenditure**

Correlation	Twitter Anxiety
Probability	
Twitter Anxiety	1,000
	–
Employment	0,342
	(0,129)
Gross Capital Formation	0,443
	(0,044)
Household Consumption Expenditure	0,433
	(0,050)

(Source: Author's estimated output)

Following this, the correlation coefficients were calculated to determine the relationships between Twitter Conviction and the alternative indicators of uncertainty. The results are analysed under the following expectations:

- Twitter Conviction: The LIWC variable indicating the degree of conviction with which statements are made, as calculated from the Twitter data (discussed in Section 4.3.2).
- Employment: Is expected to have a positive correlation with Twitter Conviction, assuming that employment increases in an environment of positive sentiment.
- Gross Capital Formation: Is expected to have a positive correlation with Twitter Conviction, since an increase in positive sentiment is expected to lead to increased capital investment by businesses.
- Household Consumption Expenditure: Is expected to have a positive correlation with Twitter Conviction as precautionary saving is expected to decline when positive sentiment increases, leading to increased consumption.

The results from Table 4.5 show that, as expected, Twitter Conviction is positively correlated with Employment. This relationship is moderately strong and statistically significant. The association between Twitter Conviction and Gross Capital Formation is also, as expected, positive, strong and statistically significant. Furthermore, in line with expectations, Household Consumption Expenditure is positively correlated with Twitter Conviction, with a strong correlation coefficient that is statistically significant. Thus, the null hypothesis is rejected in all three cases while the alternative hypothesis is accepted, indicating that there are statistically significant relationships between Twitter Conviction and the observed variables.

**Table 4.5 Results: Correlation coefficients for Twitter Conviction, Employment, Gross Capital Formation and Household Consumption Expenditure**

Correlation	Twitter Conviction
Probability	
Twitter Conviction	1,000
	–
Employment	0,669
	(0,001)
Gross Capital Formation	0,712
	(0,000)
Household Consumption Expenditure	0,785
	(0,000)

(Source: Author's estimated output)

Lastly, the correlation coefficients were calculated to determine the relationship between Twitter Uncertainty and the relevant indicators, in accordance with the following expectations:

- **Twitter Uncertainty:** The average monthly use of the words ‘uncertain’ and ‘uncertainty’ obtained from Twitter, as discussed in Section 4.2.1, converted to a quarterly frequency.
- **Employment:** Is expected to have a negative correlation with Twitter Uncertainty, under the assumption that employment will decline under circumstances of high uncertainty.
- **Gross Capital Formation:** Is expected to have a negative correlation with Twitter Uncertainty as an increase in uncertainty is expected to cause businesses to reduce their capital investment.
- **Household Consumption Expenditure:** Is expected to have a negative relationship with Twitter Uncertainty as precautionary saving increases and consumption expenditure declines.

From Table 4.6, it can be seen that the expectations of negative relationships are refuted for all variables, while all relationships are relatively weak and statistically insignificant. Thus, in all cases the null hypothesis, of no statistically significant relationship, cannot be rejected.

**Table 4.6 Results: Correlation coefficients for Twitter Uncertainty, Employment, Gross Capital Formation and Household Consumption Expenditure**

Correlation	Twitter Uncertainty
Probability	
Twitter Uncertainty	1,000
	–
Employment	0,182
	(0,431)
Gross Capital Formation	0,272
	(0,232)
Household Consumption Expenditure	0,269
	(0,238)

(Source: Author’s estimated output)

In the final step, the Twitter variables with the most significant results are compared to two benchmark tests of policy uncertainty, namely economic growth (GDP) and the existing South African policy uncertainty index developed by the NWU (NWU-PUI). Since Twitter Anxiety only shows significant results relating to Negative Emotions In News, while all other results are statistically insignificant, have signs that do not correspond with theoretical expectations and are weak in

strength, this variable is excluded from further analysis. Thus, the benchmark comparisons are only applied to Twitter Uncertainty and Twitter Conviction.

The following calculations are done with the aim of determining if Twitter, as a measurement of uncertainty, is comparable to benchmarks of uncertainty.

The correlation coefficients are first calculated for Twitter Uncertainty with the expectations of a positive correlation between Twitter Uncertainty and NWU-PUI and a negative relationship between Twitter Uncertainty and GDP.

Table 4.7 shows that, in line with expectations, Twitter Uncertainty has a strong positive correlation with NWU-PUI. Although this result is not statistically significant at the 5% level of confidence (indicating that the null hypothesis cannot be rejected), it is significant at the 10% level of confidence. The alternative hypothesis with regards to GDP is accepted as Twitter Uncertainty shows a strong negative correlation with GDP that is statistically significant at the 5% level of confidence.

**Table 4.7 Results: Correlation coefficients for Twitter Uncertainty, NWU-PUI and GDP**

Correlation	Twitter Uncertainty
Probability	
Twitter Uncertainty	1,000
	–
NWU-PUI	0,748
	(0,087)
GDP	-0,969
	(0,001)

(Source: Author's estimated output)

Finally, the correlation coefficients for Twitter Conviction were calculated under the expectations of a negative relationship between Twitter Conviction and NWU-PUI and a positive association between Twitter Conviction and GDP.

The results in Table 4.8 indicate that the expectation of a negative relationship between Twitter Conviction and NWU-PUI is refuted with a moderate relationship strength that is statistically insignificant, indicating that the null hypothesis cannot be rejected. In terms of the correlation between Twitter Conviction and GDP, the expectation of a positive correlation is confirmed with a strong correlation coefficient that is highly significant, causing the null hypothesis to be rejected in favour of the alternative hypothesis.

**Table 4.8 Results: Correlation coefficients for Twitter Conviction, NWU-PUI and GDP**

Correlation	Twitter Conviction
Probability	
Twitter Conviction	1,000
	–
NWU-PUI	0,355
	(0,490)
GDP	0,749
	(0,000)

(Source: Author's estimated output)

Based on these calculations, Twitter Uncertainty and Twitter Conviction were identified as the Twitter variables showing the most substantial results. Where Twitter Uncertainty is a measure of uncertainty derived from the average monthly use of the words 'uncertain' and 'uncertainty' on Twitter, Twitter Conviction is a measure of the degree of conviction with which statements are made on Twitter, as provided by the LIWC programme.

Although Twitter Uncertainty does not compare well to any of the uncertainty indicators in the second method, there are intriguing relationships between Twitter Uncertainty and the benchmark variables. The calculations relating to Twitter Conviction provide the most consistent results overall.

By evaluating policy uncertainty variables derived from Twitter relative to accepted indicators of policy uncertainty, the first specific objective has now been addressed in its entirety in Sections 4.3.1 and 4.3.3.

A summary of the results obtained in this section will be provided in Section 4.4, while the following sub-section focusses on the second specific objective defined in Chapter 1 (Section 1.3.2).

#### *4.3.4 Constructing a policy uncertainty index*

To address the second objective, the values of the average monthly Twitter use of the words 'uncertain' and 'uncertainty' were deducted from the LIWC 'Certain' output variable for conviction in terms of Twitter, to obtain a crude policy uncertainty index consisting only of the Twitter components:

$$PU = TC - TU \quad (\text{eq. 4.1})$$

Where  $PU$  = policy uncertainty,  $TC$  = Twitter conviction variable and  $TU$  = Twitter uncertainty variable

The expectations were that the Twitter-based policy uncertainty index will have a negative correlation with NWU-PUI as an increase in the Twitter policy uncertainty index indicates an improvement in sentiment, while an increase in the NWU's policy uncertainty index is indicative of an increase in uncertainty. For reference, the Twitter-based policy uncertainty index was also compared to the second uncertainty benchmark, namely GDP, with which it is expected to have a positive relationship.

The results shown in Table 4.9 reveal that, while the Twitter measure of uncertainty (Twitter-PUI) has a relatively strong negative relationship with NWU-PUI, this relationship is not statistically significant. Thus, the null hypothesis cannot be rejected in this case, indicating that there is no statistically significant relationship between the Twitter-based policy uncertainty index and the policy uncertainty index constructed by the NWU. However, the direction of the relationship is as expected, and the insignificance of the result could be attributed to the small sample size, since data for the NWU-PUI is only available from the third quarter of 2015. This issue was also encountered by Nisar *et al.* (2018:111) in their study, as discussed in Chapter 2 (Section 2.6).

Furthermore, in line with expectations, Twitter-PUI has a strong positive relationship with GDP, for which data was available from the fourth quarter of 2011. This relationship is also statistically significant at the 5% level of confidence, indicating that the null hypothesis can be rejected in favour of the alternative hypothesis.

**Table 4.9 Results: Correlation coefficients for Twitter-PUI, NWU-PUI and GDP**

Correlation	Twitter-PUI
Probability	
Twitter-PUI	1,000
	—
NWU-PUI	-0,616
	(0,193)
GDP	0,909
	(0,012)

(Source: Author's estimated output)

The Twitter policy uncertainty index provides monthly values of the degree of uncertainty, where a value above 0.80 shows higher certainty and a value below 0.80 is an indication of increased uncertainty. The value of 0.80 was obtained by calculating the average of 78 monthly observations of results obtained after deducting the uncertainty component from the conviction component.



The second specific objective, stated in Chapter 1 (Section 1.3.2), has thus been addressed through the construction of the basic policy uncertainty index discussed in this section.

The following section will conclude this chapter with a summary of its main findings.

#### **4.4 Results and conclusion**

Chapter 4 explained how data from Twitter was collected. During the collection process two categories of keywords were obtained. The first keyword category consisted only of the words 'uncertain' and 'uncertainty'. These keywords were used in both the first and second methods of data analysis. The second category focussed on the collection of keywords relating to the economy, regulation or policies, and the government, which were only used in the second method of data analysis. The keywords from the second category were also used to obtain data for the news variable and this process, along with the process of data collection from other sources, was also discussed.

The LIWC programme, utilised to quantify qualitative data for use in method two, was presented and its functions, relevant to this study, were explained while the applicable output variables were identified and defined.

Two methods were used to test the significance of Twitter data as a measurement of policy uncertainty. The first method entailed graphically observing the occurrences of Twitter uncertainty instances as they correspond with significant political events. From this method it can be seen that Twitter uncertainty generally coincide with political events. However, in some cases, uncertainty precedes an event and in others, occurs after an event. A possible explanation is that, in certain cases, political events are expected and discussed in the media which could lead to an early spike in uncertainty. In other instances, uncertainty can occur after the event if the effects of such an event were unexpected. Due to the complexity of determining which explanation applies or if the spikes in uncertainty are unrelated to political events, another test was done to determine how Twitter data relates to existing indicators of uncertainty, as well as benchmarks of uncertainty measurements.

The second method made use of the LIWC programme to quantify data from Twitter and news media. Three variables, relating to uncertainty, were chosen from the LIWC output, namely 'Anx', 'Certain', and 'Negemo'. These variables represent the degree of anxiety, conviction and negativity, respectively, present in a given text. The LIWC results for Twitter 'Anx' (Twitter Anxiety) and 'Certain' (Twitter Conviction), as well as the average monthly use of the words 'uncertain' and 'uncertainty' on Twitter (Twitter Uncertainty), were compared to other known measures of uncertainty, namely: The LIWC 'Negemo' result from news sources (Negative Emotions In News), the average daily prices

of the FTSE/JSE All Share Index (FTSE/JSE ALSI), employment data (Employment), short term interest rates (Short-Term Interest Rates), gross capital formation (Gross Capital Formation), final household consumption expenditure (Household Consumption Expenditure), and inflation in the form of the Consumer Price Index (CPI).

The significant Twitter uncertainty measures were then compared to two benchmarks of policy uncertainty as a further test of their relevance, namely economic growth (GDP) and the existing South African policy uncertainty index (NWU-PUI).

The comparisons were done by calculating the correlation coefficients of each Twitter uncertainty measure and the above-mentioned indicators of uncertainty and benchmarks of uncertainty measures. These results indicate that Twitter Anxiety is not a stable, relevant measure of policy uncertainty, as it only shows substantial results in relation to Negative Emotions In News. This variable was therefore excluded from further calculations. However, Twitter Conviction shows strong, statistically significant, positive relationships with the average daily prices of the FTSE/JSE ALSI, Employment, Gross Capital Formation, and Household Consumption Expenditure. Although not significantly related to the NWU-PUI, Twitter Conviction has a strong, positive and statistically significant relationship to GDP. While Twitter Uncertainty only shows a statistically significant and weak positive relationship with CPI, it does have a strong negative relationship with GDP that is statistically significant. Although the relationship between Twitter Uncertainty and NWU-PUI is strong and positive, it is only significant at the 10% level of confidence. However, as mentioned in Section 4.3.4, the results relating to NWU-PUI could be affected by the small sample size available. For this reason, the Twitter uncertainty measures were also compared to the second uncertainty benchmark, namely GDP.

The results obtained in method one and two relating to Twitter Uncertainty indicate noteworthy relationships between Twitter Uncertainty and political events and the benchmarks of uncertainty measures. Although the calculations in the second method show significantly more promising relationships between Twitter Conviction and the alternative indicators, the combination of the results for Twitter Uncertainty and Twitter Conviction from the first and second methods indicate that Twitter can conceivably be used as a proxy for policy uncertainty.

Based on these results, a basic policy uncertainty index was constructed which indicates that by using the Twitter Conviction and Twitter Uncertainty variables to determine the degree of uncertainty, a Twitter component of policy uncertainty can be computed to supplement existing measures of policy uncertainty.

The findings presented in this chapter have addressed the first and second specific objectives, stated in Chapter 1 (Section 1.3.2) by, firstly, demonstrating that markers of uncertainty from Twitter show trends concurrent with major political events. It was also shown that Twitter data is related to many of the accepted indicators of policy uncertainty as well as benchmarks of uncertainty measures. Finally, a simple policy uncertainty index, consisting only of Twitter data, was constructed and compared to the established benchmarks of uncertainty. The results from these tests support the possibility that Twitter can provide further insight into policy uncertainty.

Based on the findings in Chapter 4, Chapter 5 will discuss the conclusions reached in this study, the limitations encountered and recommendations for further studies. The third, specific objective, stated in Chapter 1 (Section 1.3.2), will also be addressed.

## **CHAPTER 5**

### **CONCLUSIONS, LIMITATIONS AND RECOMMENDATIONS**

#### **5.1 Introduction**

In accordance with the three main objectives of research, as outlined by Babbie (2011:95-97) in Chapter 2 (Section 2.1), and the undertaking of this study to use these objectives as a guideline, the following was achieved during the course of this study:

1. Exploration was done relating to the use of social media, in the form of Twitter in measuring policy uncertainty. This aided in addressing the objectives set at the start of this study, brought avenues of further research to light and provided methods on which further studies can be built.
2. This study also observed the relationship between Twitter measurements of uncertainty and various alternate indicators of uncertainty and benchmarks of uncertainty measurements, which were then described.
3. In addition, the results obtained were explained during the processes followed.

The final chapter of this study will summarise the conclusions reached based on the objectives stated in Chapter 1 (Section 1.3) and the results obtained during the course of this research. The limitations of the study as well as recommendations for future research will also be discussed.

#### **5.2 Conclusions**

In recent years, the topic of policy uncertainty has been receiving increased attention due to its adverse impact on economic growth. This is attributed to the fact that policy uncertainty can affect interest rates and can lead to lower employment, higher inflation, lower levels of household consumption, declines in investment and industrial production, and lower exports. The effects of policy uncertainty are also more prominent in developing countries than in developed countries and can determine the severity of recessions and influence the strength of recovery.

In South Africa, the effects of policy uncertainty manifest in the form of lower private sector expenditure on research and development, higher unemployment, higher inflation, and declining commodity prices. These effects ultimately obstruct economic growth and emphasise the importance of policy uncertainty.

The economic consequences of policy uncertainty highlight the importance of being able to accurately measure policy uncertainty. Such a measurement will assist policymakers in evaluating the reception of policy proposals, in implementing the lessons learned and in formulating future policies while providing support in terms of economic forecasting. An accurate measure of policy uncertainty will also benefit various economic participants such as economists, financial planners and firms who will be able to use this information to improve business processes, for example budgeting, financial planning, managing financial expectations and procurement.

As the importance of being able to measure policy uncertainty has increasingly been realised, a variety of studies has emerged that provide insights into this subject. These studies suggest that policy uncertainty is mainly measured through a method that involves the collection of keywords principally relating to the words 'economic', 'policy' and 'uncertain'. Further variables used include other accepted indicators of uncertainty such as: Stock market volatility, expert opinions, the amount of cash held by firms, gross capital formation, the cross-sectional spread of firm- and industry-level earnings, investment, forecaster disagreement, volatility indices, household saving and expenditure, interest rates, the number of tax provisions expected to expire in the near future, data from news media, employment, productivity growth, inflation, and political events. These measures are also compared to benchmarks such as economic growth, recessions, and other policy uncertainty indices to test the validity of their measurements.

Social media has become a major part of the structure of social interaction and similarly have gained popularity as a source of data in academic research. With the Internet becoming increasingly available, more people also have access to social media. This provides a relatively new and exceptionally large source of data that has only recently been gaining momentum for use in academic studies. Social media is especially useful for sentiment analysis as it provides a platform for individuals to voice their opinions, enables them to become more politically active, and aids in the inclusion of social groups that might otherwise have been unable or disinclined to participate. To this extent, previous studies have shown that stock market price movements can be predicted by social media, while other studies use social media to demonstrate that socio-economic events significantly affect the public mood.

In South Africa, the use of social media is also on the rise. Although Internet access has been an obstacle to some social media users, there are developments underway (such as Project Isizwe)

that aim to establish free Internet zones for low income communities. Some social media platforms have also developed versions of their applications that require less data for installation and are accessible even with poor network coverage. Social media has especially been increasingly used as a tool for public activism in South Africa, while various South African government departments also have social media profiles that are used for communication purposes. Social media has also become a popular method to access news media in South Africa. Additionally, the emergence of smartphones has contributed greatly to the advancement of Internet access, making it easier for the average South African to use social media.

In terms of social media, Twitter is the most popular platform used for engagement in public discourse in South Africa. There is also a great variety of applications that have been developed with the specific aim of obtaining information from Twitter, which contribute to making it a valuable source of data for academic research purposes. Twitter holds many advantages that makes it ideal as a source of data, such as, the large amount of data available, the ease of access, the multitude of available tools and applications that facilitate the procurement and analysis of data, the fact that real-time data can be obtained, and that it provides a direct channel to public opinion. There are, however, possible obstacles that may be encountered when using Twitter as a source of data such as, ethical issues, the fact that not all South Africans use Twitter, language constraints, the erroneous exclusion of relevant search terms or the inclusion of irrelevant content, methodological difficulties that are as yet unknown, and the possibility that context may be lost when using automated analysis tools.

Based on the importance of policy uncertainty to the South African economy and the value of Twitter as a tool for sentiment analysis, the general goal of this study was provided in Chapter 1 (Section 1.3.1), namely: “To analyse social media, in the form of Twitter, as a measure of policy uncertainty and an additional input into a policy uncertainty index.” To achieve the main objective, three specific objectives were also outlined in Chapter 1 (Section 1.3.2) which are: 1) To determine the feasibility of Twitter as a measurement of policy uncertainty by evaluating Twitter data trends against significant political events and accepted indicators of policy uncertainty; 2) to construct a basic policy uncertainty index, using the data obtained from Twitter, and to compare this index with the existing South African policy uncertainty index; and 3) to provide guidelines to policymakers on how to respond to policy uncertainty, based on the insights gained from objectives two and three.

The first two specific objectives were addressed in Chapter 4, while the third and final specific objective will be discussed in the current chapter.

The following subsections summarise the conclusions reached in terms of each specific objective.

### *5.2.1 The feasibility of Twitter as a measurement of policy uncertainty*

The first specific objective was addressed in Chapter 4 (Sections 4.3.1 and 4.3.3) by means of two methods of data analysis.

The first method entailed presenting the occurrences of the words 'uncertain' and 'uncertainty' in a graph relative to major political events to determine if there are trend similarities between the two sets of data. The resulting graphs (shown in Annexure A, Figures A1 to A3) indicated that the use of the words 'uncertain' and 'uncertainty' on Twitter tends to occur in conjunction with significant political events, indicating that there is a relationship between political events and uncertainty.

In the second method, the respective correlation coefficients were calculated between three Twitter variables and indicators of policy uncertainty. The Twitter variables are the LIWC outputs for anxiety (Twitter Anxiety) and certain (Twitter Conviction), and the average of the monthly use of the words 'uncertain' and 'uncertainty' (Twitter Uncertainty). While the indicators of policy uncertainty are: The LIWC output for negative emotions used in news articles (Negative Emotions In News), short-term interest rates (Short-Term Interest Rates), the inflation rate (CPI), average daily stock market prices (FTSE/JSE ALSI), employment (Employment), gross capital formation (Gross Capital Formation), and final consumption expenditure by households (Household Consumption Expenditure).

The results from the second method showed that Twitter Anxiety is not a significant indicator of policy uncertainty. However, Twitter Uncertainty shows a weak, statistically significant, and positive relationship with CPI. Twitter Conviction, on the other hand, shows very promising results with strong, statistically significant, and positive relationships to the average daily prices of the FTSE/JSE ALSI, Employment, Gross Capital Formation (as a proxy for investment), and Household Consumption Expenditure.

When compared to the benchmark measurements, neither Twitter Conviction nor Twitter Uncertainty is statistically significantly related to the NWU's policy uncertainty index (NWU-PUI). However, the results relating to the data from the NWU policy uncertainty index could have been affected by the small sample size available. Nonetheless, both variables show strong, statistically significant relationships to GDP, where Twitter Conviction is positively correlated with GDP and Twitter Uncertainty is negatively correlated with GDP.

The first specific objective of this study entailed two parts; both of which used different methods of data analysis. The first part focused on comparing data from Twitter to significant political events, which was done by means of the first method of data analysis. The second part focused on evaluating Twitter data relative to accepted indicators of policy uncertainty, using the second method

of data analysis. The results from the two methods of data analysis indicate that Twitter does provide information regarding policy uncertainty. Thus, the first specific objective was satisfied.

### *5.2.2 Constructing a Twitter-based policy uncertainty index*

In Chapter 4 (Section 4.3.4), the second specific objective was also achieved through the construction of a basic policy uncertainty index that shows the degree of policy uncertainty on a monthly basis. Movement of the index above 0.80 indicates increased policy certainty, while movement below 0.80 is indicative of increased policy uncertainty. The index was created by subtracting the values of the Twitter uncertainty data series from the Twitter conviction values to obtain a certainty result.

However, this policy uncertainty index is not intended to be used as an individual index. Rather its purpose is to demonstrate that Twitter data can be used, in conjunction with existing measures of policy uncertainty, to provide information about policy uncertainty.

From the results obtained in pursuit of the first specific objective, it can be seen that Twitter does not provide all-encompassing information about policy uncertainty. The results only indicate that Twitter can provide information about policy uncertainty. However, as seen from the literature reviewed in Chapter 2, the accuracy of a policy uncertainty index based on social media data will be greatly improved when combined with other measures of policy uncertainty. These measures include: News data, expert opinions, volatility indices, forecaster disagreement, productivity growth, stock market volatility, the amount of cash held by firms, gross capital formation, the number of tax provisions expected to expire in the near future, inflation, political events, the cross-sectional spread of firm- and industry-level earnings, interest rates, household saving and expenditure trends, investment and employment.

### *5.2.3 Guidelines for policymakers*

While the first two specific objectives were addressed in the preceding chapters, the third specific objective is based on the collective conclusions reached throughout this study, deeming it appropriate for discussion in this final chapter.

Thus, this section will attend to the final specific objective by providing guidelines to policymakers on how to use the information provided by policy uncertainty indices to respond appropriately to policy uncertainty and to create future policies.



As seen in previous chapters, policy uncertainty can have a profoundly negative impact on a country's economy. Chapter 1 introduced the obstacles that the South African economy is facing due to policy uncertainty and highlighted the importance of being able to accurately measure policy uncertainty.

Chapter 2 discussed the impact of policy uncertainty on vital economic determinants, from which it is evident that policy uncertainty is a subject deserving of the increased attention that it has been receiving in recent years. Chapter 3 elaborated on the effects of policy uncertainty on the South African economy through its impact on unemployment, the expenditure by the private sector on research and development, and economic growth. Special attention was also given to current issues in South Africa that can intensify policy uncertainty, such as the proposed changes to policy in the mining industry and land expropriation, as well as high inflation and threats of further downgrades by ratings agencies. Thus, policy uncertainty is a major source of concern to the South African economy.

Chapter 4 showed that social media in the form of Twitter can provide further information relating to policy uncertainty in the South African macro-economic environment. This was established by showing that Twitter uncertainty measures coincide with movements in accepted alternate indicators of policy uncertainty.

Owing to the economic consequences of policy uncertainty, it is imperative that policymakers consider the effects that the timing, type, method, and clarity of communication, as well as the perceived motives of their policies can have on public sentiment. The possible effects of every new policy should be considered based on current levels of policy uncertainty, especially since, under circumstances of high policy uncertainty, drastic new policies – or changes to policies – could serve to heighten policy uncertainty which, in turn, could lead to a general mistrust of authority and the possible failure of future policies. Chapter 2 also emphasised the importance of a stable, predictable economic environment for the promotion of investment. Policymakers should keep this in mind when formulating policies and should be cautious of policies that will be seen as sudden shocks.

As seen from the events of December 2015, discussed in Chapters 1 and 3, it is difficult to mitigate policy uncertainty in the short term, as a simple reversal of the policies that caused uncertainty can serve to only increase policy uncertainty. To this extent, it is preferable to avoid policy uncertainty or, if drastic policies are needed, to consider the timing of announcements, and methods of communication and implementation to mitigate the effects of policy uncertainty. Increased transparency through communication could thus aid in alleviating policy uncertainty.

An informative policy uncertainty index for South Africa, which includes data from Twitter, can assist policymakers in this regard, by providing them with information about the reception of previous policies and the current level of policy uncertainty. Such an index will allow them to determine the suitability of their policies and to judge the correct timing for the announcement of new policies. Based on the role that social media plays in the circulation and discussion of news, the government could also increase efforts to clearly communicate policy implementation and changes on social media with emphasis on the motives and expected outcomes of such policies. By allowing the public to comment on the proposed policies on social media and by answering frequently asked questions, policy uncertainty could be alleviated, while policymakers will also receive valuable feedback.

### **5.3 Limitations**

The principal limitation of this study was the fact that Twitter data for the identified keywords were only available from June 2010. Further data constraints were also encountered with respect to some of the indicators of policy uncertainty as only quarterly data was available for some variables, and then only from the fourth quarter of 2011. In this regard, it should be noted that, according to Nisar *et al.* (2018:111), a small sample size can affect the results of correlation analysis.

The low amount of observations available also limited the range of empirical methods that could be applied. This was seen in the construction of autoregressive distributed lag models (ARDL) that rendered incoherent results and were therefore not included in the study.

Furthermore, although correlation is indicative of an association between variables, the correlation coefficient does not provide information about causality. This limits the scope within which conclusions can be made from the results but provides an opportunity for further study.

Another limitation of this study is that a proficiency in computer coding would have been of considerable advantage to the research process. While there are many Twitter applications that provide the ability to collect tweets daily, or even up to a few months of historical data, there are almost no applications that incorporate the ability to automatically obtain historic data from past years. Although, as stated, knowledge of computer coding is not a prerequisite to using Twitter for academic research, it could have served to add value to this study. This encountered limitation therefore enables the current study to contribute to the knowledge base on using Twitter for academic research purposes by identifying a methodological constraint (and thus addressing one of the disadvantages of using Twitter for academic data as stated in Chapter 3 (Section 3.4.2)).

A further limitation was brought about by another one of the disadvantages of using social media as a source of data, as discussed in Chapter 3 (Section 3.4.2), which is the potential loss in context brought about by the LIWC programme. Although most of the possible errors should be marginalised by the correct classification of overall emotion based on the normal use of words, the magnitude of such errors is not quantifiable.

The following section will discuss the recommendations for future research based on this study.

#### **5.4 Recommendations for further study**

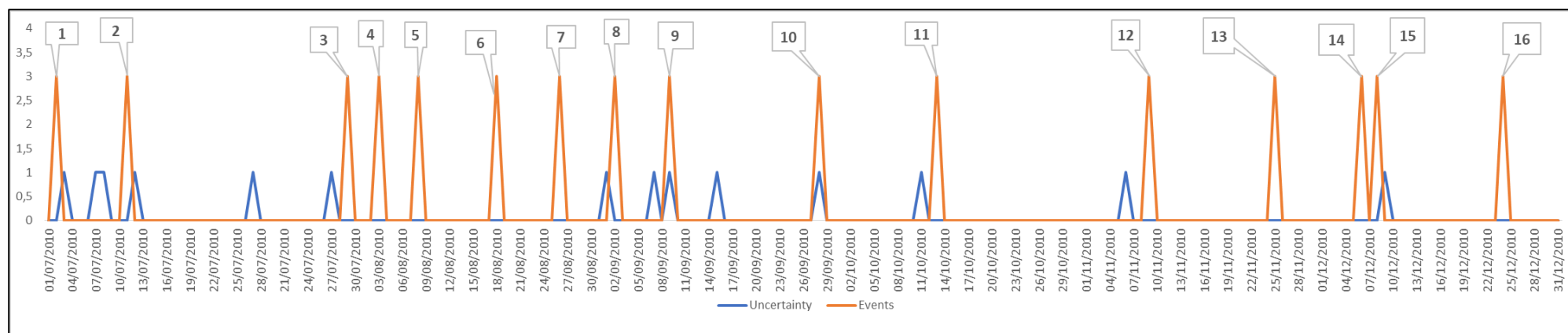
The aim of this study was to determine the possibility of using Twitter as a measure of policy uncertainty. From the results obtained, a framework has emerged for future developments.

Thus, using this study as a basis, future research should improve its accuracy by incorporating knowledge of computer coding to create a programme specifically applied towards its objectives. In this manner, the use of the LIWC programme can be excluded to use only the frequency of certain keywords, or the applicable functions from LIWC can be incorporated into the new programme. This application can also be programmed to conduct all calculations so that the collection and analysis of data are all managed by one programme, which then provides a monthly policy uncertainty result.

As more data becomes available, future studies can also review the accuracy of the results obtained in this study by applying statistical methods, such as ARDL models, which were not suited to this research due to data availability constraints.

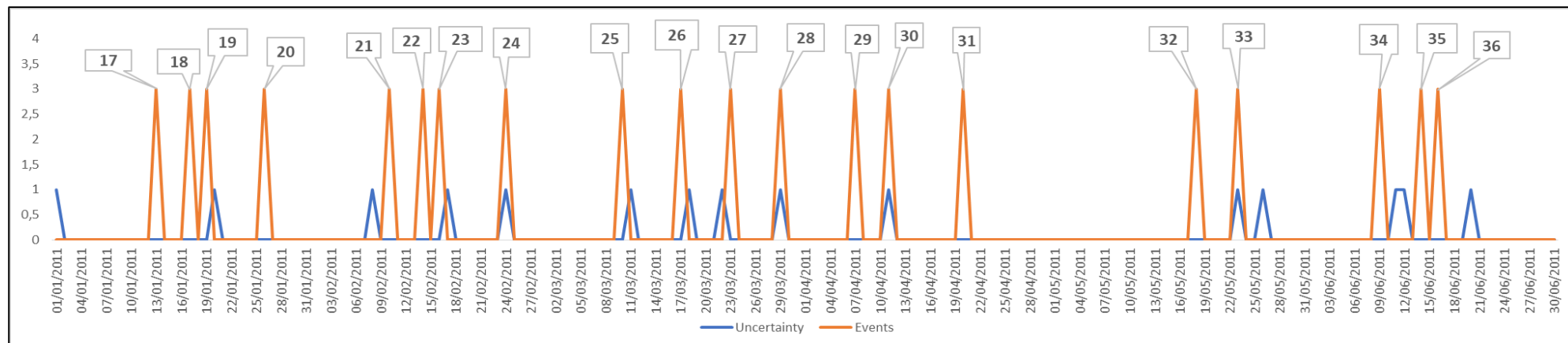
## ANNEXURE A

The following figures represent the occurrences of the words ‘uncertain’ and ‘uncertainty’ relative to significant political- and social-economic events, as discussed in Chapter 4 (Section 4.3.1), as part of the first method of data analysis. This method is based on the studies by Bollen *et al.* (2010:4, 2011:453) discussed in Chapter 2 (Section 2.6). The words ‘uncertain’ and ‘uncertainty’ were obtained from Twitter between the period of 01 July 2010 to 31 December 2011, while the information regarding significant events were obtained for the same period on a monthly basis from various news webpages.



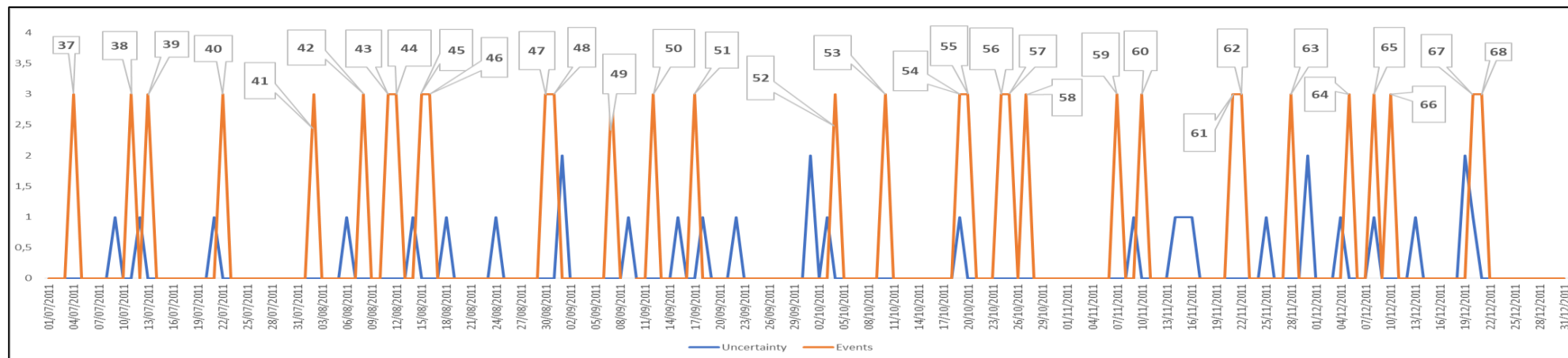
**Figure A1 Uncertainty and political events 01 July 2010 to 31 December 2010**

(Source: Author's own calculations based on various news reports)



**Figure A2 Uncertainty and political events 01 January 2011 to 30 June 2011**

(Source: Author's own calculations based on various news reports)



**Figure A3 Uncertainty and political events 01 July 2011 to 31 December 2011**

(Source: Author's own calculations based on various news reports)

**Table A1 Keys for Figures A1, A2 and A3**

<b>Symbol</b>	<b>Date</b>	<b>Event</b>	<b>Symbol</b>	<b>Date</b>	<b>Event</b>
<b>1</b>	02/07/2010	Police Commissioner found guilty of corruption	<b>7</b>	26/08/2010	Civil servants' demonstration
<b>2</b>	11/07/2010	Education Summit	<b>8</b>	03/09/2010	Special status of illegal Zimbabwean immigrants withdrawn. Deportations to begin after December 31. And striking state workers protested
<b>3</b>	29/07/2010	President Jacob Zuma announced that South Africa would stop recognising half the nation's traditional kings and queens	<b>9</b>	09/09/2010	Crime statistics released
<b>4</b>	03/08/2010	Former National Police Chief sentenced to 15 years in jail for corruption	<b>10</b>	28/09/2010	Cash threshold reporting obligations imposed by the Financial Intelligence Centre Act (FICA) to take effect
<b>5</b>	08/08/2010	Journalists launched campaign against proposed media regulations	<b>11</b>	13/10/2010	Residents of Madelakufa squatter camp protested, demanding houses
<b>6</b>	18/08/2010	Civil servant strike	<b>12</b>	09/11/2010	Minister of Police press statement on violent crime published

<b>Symbol</b>	<b>Date</b>	<b>Event</b>	<b>Symbol</b>	<b>Date</b>	<b>Event</b>
<b>13</b>	25/11/2010	Anti-corruption unit launched to investigate government officials misusing funds and receiving bribes	<b>21</b>	10/02/2011	State of the Nation Address (SONA) 2011
<b>14</b>	06/12/2010	New Age newspaper denied being an agent of the African National Congress (ANC)	<b>22</b>	14/02/2011	Strikes and strike violence occurred
<b>15</b>	08/12/2010	President Jacob Zuma announced R210 million credit package for Cuba and wrote off Cuba's debt	<b>23</b>	16/02/2011	Protests about ANC councillor nominations took place
<b>16</b>	24/12/2010	Minister of International Relations and Cooperation announced SA's invitation to join 'BRIC' grouping	<b>24</b>	24/02/2011	State mining company launched
<b>17</b>	13/01/2011	National Skills Development Strategy (NSDS) III Launched	<b>25</b>	10/03/2011	Possibility of drinking age raised to 21 announced
<b>18</b>	17/01/2011	Talk of nationalising Postbank	<b>26</b>	17/03/2011	Rumours of Hawks vulnerability to political interference
<b>19</b>	19/01/2011	Crime statistics published; Mr. Solly Mokoetle resigned as (South African Bureau of Standards) SABS chief executive officer	<b>27</b>	23/03/2011	Electricity price was increased amidst threats of blackouts
<b>20</b>	26/01/2011	Announcement: Number of farms and agriculture's contribution to employment dropped	<b>28</b>	29/03/2011	New traffic unit launched



<b>Symbol</b>	<b>Date</b>	<b>Event</b>	<b>Symbol</b>	<b>Date</b>	<b>Event</b>
<b>29</b>	07/04/2011	Start of Pikitup Strike	<b>35</b>	14/06/2011	SA president lashed out at the North Atlantic Treaty Organisation's (NATO) support of resolution authorising protection of civilians in Libya civil war
<b>30</b>	11/04/2011	African National Congress Youth League (ANCYL) member appeared in court on hate speech charges	<b>36</b>	16/06/2011	The Swedish arms-maker Saab allegedly paid more than \$3 million to ANC defence consultant
<b>31</b>	20/04/2011	State of cities report released	<b>37</b>	04/07/2011	Metal workers strike
<b>32</b>	18/05/2011	Municipal elections	<b>38</b>	11/07/2011	Oil refinery workers joined strike amidst fears of fuel shortages
<b>33</b>	23/05/2011	Election results published	<b>39</b>	13/07/2011	National Union of Mineworkers (NUM) said wage talks are deadlocked and that they are preparing for a strike
<b>34</b>	09/06/2011	National Planning Commission report released with several negative challenges facing SA	<b>40</b>	22/07/2011	De Beers diamond miners strike and Deputy President Kgalema Motlanthe said South Africa's education standards are too low

<b>Symbol</b>	<b>Date</b>	<b>Event</b>	<b>Symbol</b>	<b>Date</b>	<b>Event</b>
<b>41</b>	02/08/2011	SA agreed to a R2.5 billion loan to Swaziland	<b>49</b>	07/09/2011	Centre for Development and Enterprise (CDE) report released
<b>42</b>	08/08/2011	Bus drivers strike	<b>50</b>	12/09/2011	ANC to appeal court decision on 'shoot the boer' song
<b>43</b>	11/08/2011	Municipal services announced strike intention	<b>51</b>	17/09/2011	Protests took place over secrecy bill
<b>44</b>	12/08/2011	Archbishop Emeritus Desmond Tutu called for 'wealth tax' to be imposed on all white South Africans	<b>52</b>	04/10/2011	Dalai Lama's visa application rejected
<b>45</b>	15/08/2011	National Health Insurance (NHI) proposal approved	<b>53</b>	10/10/2011	The National Census was launched and government spending was criticised in the news
<b>46</b>	16/08/2011	President Jacob Zuma nominated Mogoeng as Chief Justice at the time when alleged corrupt post office executives were probed	<b>54</b>	19/10/2011	ANCYL President made a racist comment toward Indians
<b>47</b>	30/08/2011	ANCYL protests took place and Parliament wrote off debt of MP's implicated in Travelgate scandal	<b>55</b>	20/10/2011	Foreigners threatened by residents of a Johannesburg township for living in RDP houses
<b>48</b>	31/08/2011	Draft green paper on land reform released	<b>56</b>	24/10/2011	Police chief and cabinet minister suspended for corruption

<b>Symbol</b>	<b>Date</b>	<b>Event</b>	<b>Symbol</b>	<b>Date</b>	<b>Event</b>
<b>57</b>	25/10/2011	Growth forecast revised down to 3.1%	<b>63</b>	28/11/2011	United Nations (UN) climate negotiations opened in Durban
<b>58</b>	27/10/2011	ANCYL protests occurred and the Democratic Alliance (DA) party elected a parliamentary caucus leader	<b>64</b>	05/12/2011	Police fired rubber bullets at protestors against SA's alleged involvement in fraud in the November election in the Democratic Republic of the Congo (DRC)
<b>59</b>	07/11/2011	Negative development report by Development Bank of Southern Africa (DBSA)	<b>65</b>	08/12/2011	Presidency released the Donen Commission Report – Investigating if SA laws were broken during UN Oil for Food scandal
<b>60</b>	10/11/2011	ANC dismissed youth leader Mr. Julius Malema	<b>66</b>	10/12/2011	ANC offered to help Zimbabwe African National Union – Patriotic Front (ZANU-PF) win next elections in Zimbabwe
<b>61</b>	21/11/2011	Black Tuesday protest declared against 'secrecy bill'	<b>67</b>	20/12/2011	Suspended youth leader, Mr. Julius Malema, elected to ANC senior party post in Limpopo
<b>62</b>	22/11/2011	ANC pushed bill through parliament to protect state secrets	<b>68</b>	21/12/2011	ANC Limpopo plans for land expropriation and nationalisation of mines: Compensation to be paid only on improvements. And President Zuma berated Christianity for orphans and old age homes

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