# A Descriptive Narrative of Economic Policy Uncertainty in South Africa

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## 1. Introduction

The aim of this paper is to provide a descriptive narrative of economic policy uncertainty in South Africa since . . . To this end, an EPU index is constructed using text data from online news sources. One of the aims is to provide a

## 2. Economic policy uncertainty in existing literature

Existing literature provide several definitions of uncertainty. In general terms, Jurado, Ludvigson, and Ng (2015) define uncertainty as volatility in shocks that cannot be forecasted by economic agents. Bloom (2014) echo this by describing uncertainty as a concept that occupies the minds of agents in relation to possible future events. More specifically, Baker, Bloom, and Davis (2016) define economic policy uncertainty not only as uncertainty about policies as such, but also about who is making policy decisions and the effects thereof. It is important to note that uncertainty is defined in terms of all agents in the economy - as stated by Bloom (2014) - consumers, managers and policymakers. The remainder of this paper will thus refer to EPU at this aggregated level.

The sole purpose of this paper is to provide a narrative of the evolution of economic policy uncertainty in South Africa that is heavily supported by descriptive analysis. An obvious extension to this research is to investigate the impact of uncertainty on key variables of interest. Albeit not within the scope of this paper, it is still pertinent to motivate the rationale for constructing a measure of EPU by

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looking at the relationships existing literature have uncovered. A delineation between a macro- and microeconomic focus is immediate in this literature. This paper will suffice with motivating the usefulness of a measure for EPU by referring to this literature below.

In terms of the microeconomy, Bachmann, Elstner, and Sims (2013) find that there is a decline in production and employment in response to a shock in EPU. Bloom (2014) echoes that the level of uncertainty at a microeconomic level (i.e. individual industries, firms and plants) is usually higher during times of economic recessions. However, not sufficiently controlling for the economic conditions that can also influence production and employment can confound the estimate of the impact of EPU on these variables. To this end, Caggiano, Castelnuovo, and Groshenny (2014) show that not taking into account that uncertainty shocks occur mostly in economic recessions, leads to an underestimation of the negative relationship between uncertainty and unemployment. It is immediate that aggregating the industry/firm level effects will feed into the macroeconomy.

At the macroeconomic level, Baker, Bloom, and Davis (2016) find that rising uncertainty in the United States is a leading indicator for declining investment, production and employment. However, since the global financial crisis (GFC), most macroeconomic literature pertaining to uncertainty have been concerned with linkages to financial markets. Caldara et al. (2016) go as far in stating that the interaction between uncertainty and financial shocks is "toxic" and that the GFC was likely due to an acute manifestation of this. Other scholars establish relationships between EPU and the equity option market (Kelly, Pástor, and Veronesi 2016), increased stock price volatility (Baker, Bloom, and Davis 2016) and increased risk premia (Pástor and Veronesi 2013).

The above discussion illustrates the usefulness of a measure for EPU. It now remains to be ascertained how exactly to measure it. Earlier literature (see e.g. Bachmann, Elstner, and Sims (2013)) made use of survey data and constructed an EPU index by measuring the discrepancies between respondents' answers to forward-looking questions. Redl (2015) takes an alternative approach, employing inter alia data from professional forecasting competitions and scrutinising official economic reviews released by the South African Reserve Bank to construct an EPU index.

More recently, a novel approach by Baker, Bloom, and Davis (2016) garnered academic praise and an increasing number of scholars followed suit. The approach developed by Baker, Bloom, and Davis (2016) gauge EPU by extracting information from newspaper articles. The most basic index is constructed using the frequency of articles containing words related to uncertainty. Refinements on the basic index attempt to, inter alia, control for linguistic modality (Tobback et al. 2018), eliminate the need for human classification of articles by using support vector machines (Azqueta-Gavaldón 2017) and provide a greater level of disaggregation in terms of policy categories (Baker, Bloom, and Davis 2016). The methodologies of these papers are not discussed here as it overlaps greatly with the methodology discussed in section 3.2.

## 3. Constructing a set of Uncertainty Indices for South Africa

### *3.1. Data*

The aim of this paper is to capture uncertainty in the South African economy as reported by newspaper articles. The aim is to provide a set of indices describing the evolution of uncertainty which can be used to uncover relationships such as those reviewed in section 2. This requires that any potential data sources meets a set of criteria. First, the sources have to be South African and cover predominantly South African events. Second, the sources have to be available for a significant period so as to be able to extract the evolution of uncertainty over time. Finally and most importantly, the articles forming part of any potential data source have to reach a large proportion of the economic decisionmakers. This criterium improves the probabality of observing the type of relationships reviewed in section 2.

From all the potential data sources available, Sabinet meets all the requirements stemming from the aim of this paper. This online database hosts multiple newspapers and periodicals from 1978. Three newspapers in particular meet the third criterium stated above. With a readership of approximately 500 000, the *Sowetan* represent a large readership throughout South Africa. Second, with a readership of approximately 80 000, the *Business Day* is specifically aimed at financial matters. Finally, focussing on news in the financial and political space, the *Financial Mail* has an average readership of 40 000 (Odendaal and Reid 2018). The focus of the *Business Day* and the *Financial Mail* specifically makes it appropriate as it meets the first criterium imposed on the data source.

The final dataset was constructed by Odendaal and Reid (2018) who downloaded PDFs of the digital scans of articles in the three newspapers from the Sabinet online database. These files were converted to raw text format using PDFTOOLS (Ooms 2017). The final dataset comprises 178688 articles in the three newspapers from January 2004 till October 2017. The *Business Day* newspaper constitutes the largest contribution with 117 169 articles, the *Sowetan* 37 403 articles and the *Financial Mail* the remaining 24 116 articles.

### *3.2. Methodology*

In order to build an uncertainty index, the newspaper articles discussed in section 3.1 is scrutinised. This paper presents two sets of indices - the naive and the refined - both following the same methodology. The delineating factor is the way in which the uncertainty score for each article is calculated. As such, this calculation for the respective uncertainty scores is discussed before explaining the general methodology of constructing the indices.

### *3.2.1. Calculating uncertainty scores*

For the naive approach, the uncertainty score is simply a binary variable that is equal to one if the article contains the word "uncertain" at least once and zero otherwise. Albeit being able to quantify uncertainty to an extent, the naive index is rigid in its application. Tobback et al. (2018) state that every article matching the aforementioned criteria forms part of the naive index, regardless of the entity that the uncertainty is related to. To control for this, the naive index is calculated for uncertainty pertaining to specific topics. This is achieved by identifying a subset of the articles pertaining to specific topics. This is discussed in further detail in section 3.2.2.

A further shortcoming of the naive index is that articles are weighted equally, i.e. all articles containing the word "uncertain" contribute one towards the uncertainty score. In reality, there is a range of words that can convey uncertainty and not all articles convey the same level of uncertainty. Therefore, the refined uncertainty index evaluates the raw text data for words contained in the Loughran and Mcdonald (2016) uncertainty dictionary. This dictionary consists of 297 words relating to uncertainty and thus provides a more comparitive measure of sentiment (Loughran and Mcdonald 2016). Measuring the score in this manner yields a continuous variable with each article's contribution to the monthly uncertainty score equivalent to this score.

### *3.2.2. Identifying topic specific uncertainty*

This paper presents four sets of uncertainty indices - monetary policy, fiscal policy, financial markets and political uncertainty. To identify each of these topics, the articles are searched for a set of keywords pertaining to each topic. These keywords, displayed in table 3.1, were decided based on a combination of existing literature (inter alia Hardouvelis et al. (2018) and Redl (2015)) and own initiatives. Only articles that contain at least one of the keywords are included in the subset for the calculation of a specific index.

Table 3.1: Keywords per Index category

| | Monetary Policy | Fiscal Policy | Financial markets | Political |
|---|---|---|---|---|
| 1 | Econom | Econom | Econom | Econom |
| 2 | policy | policy | policy | policy |
| 3 | price | fiscal | debt | ANC |
| 4 | inflation | parliament | financ | party |
| 5 | monetary | legislation | stock | political |
| 6 | committee | minister | JSE | president |
| 7 | oil | budget | market | election |
| 8 | shock | financ | exchange | vote |
| 9 | SARB | speech | rand | government |
| 10 | interest | government | interest | parliament |
| 11 | rate | bill | bank | shuffle |
| 12 | repo | tax | bond | cabinet |
| 13 | review | VAT | invest | poll |
| 14 | hike | downgrade | rate | downgrade |
| 15 | increase | debt | FDI | junk |
| 16 | decrease | rating | sovereign | legislation |
| 17 | lower | credit | rating | rating |
| 18 | | expenditure | credit | credit |
| 19 | | spending | | |

### *3.2.3. Constructing the indices*

Having demonstrated the different ways in which the naive- and refined approach measure the uncertainty score and how topic specific data subsets are identified, it is now shown how these scores are translated into an index. As mentioned, the methodology to calculate the naive- and refined index are exactly the same. The only difference between the two types of indices, is the way in which the uncertainty score is measured as illustrated in section 3.2.1. As such the general methodology as developed by Baker, Bloom, and Davis (2016) is explained.

To ease the discussion, the explanation will focus on the monetary policy uncertainty index[1]. As alluded to earlier, the monetary policy data subset is defined so as to contain only articles with at least one of the keywords of the monetary policy category, i.e. one of the 17 keywords in table 3.1. From this data subset, 17 individual subindices are constructed - a subindex for every keyword. This is achieved by applying an additional filter on the data subset: working sequentially, the data subset is

[1]This is of course arbitrary and all four indices are constructed in the same manner.

filtered to articles containing one keyword at a time. This step thus provides 17 filtered data subsets that relate to each of the 17 keywords in the monetary policy uncertainty category.

A daily uncertainty score is calculated as the mean score of the articles in the filtered data subset[2]. The daily uncertainty is aggregated to a monthly score by once again calculating the mean of the daily uncertainty scores. Finally, the monthly uncertainty score is scaled which provides the index for every keyword.

The above explanation can be framed mathematically as follows: Denote an article as $a_{jit}$ and define its uncertainty score as $us_{jit}$ where $j$ denotes the article, $i$ the day and $t$ the month. The mean uncertainty score per article constitutes the daily uncertainty score, $\frac{\sum_{j=1}^{J} us_{jit}}{J} = US_{it}$. The monthly score is calculated as the mean of the daily uncertainty scores per month, $\frac{\sum_{j=1}^{J} US_{it}}{I} = US_t$. The scaled version of this makes out the final indices.

Recall that there are still a number of indices for every topic (i.e. 17 indices relating to monetary policy, 19 to fiscal policy, 18 to financial markets and 18 for political uncertainty). Looking at 17 different indices to guage monetary policy uncertainty is impossible. Therefore, a composite index from all of the keywords are built employing principal component analysis. The first component uncovered, is equal to the composite monetary policy uncertainty index.

At this point in time, it is necessary to review how the results will look like. Recall that every index is calucalted in two ways: the naive and refined manner. As such, there are two sets of indices for every topic in table 3.1. Each set consists of a subindex for every keyword relating to every topic and from these subindices one composite index is calculated.

### *3.3. Results*

## 4. The evolution of Economic Policy Uncertainty in South Africa

Observing figures **??** to **??** showing the composite naive index in grey and the refined index in colour, highlights the similarities in the results. The main difference between the indices is that the refined index is, as the name suggests, more refined. In all cases, the refined index is less volatile than its naive counterpart and shocks are less persistent. For this reason, the remaineder of this paper works solely with the refined composite index.

Figures **??** to **??** also show the similarity in peak periods across the four topics. To test this formally, a structural break test was performed on each composite index to identify whether significant

[2]Calculating the mean controls for the volume of articles varying per day.

shifts in uncertainty is common across topics[3]. From these results, two distinct periods are identified (highlighted panels in figures **??** to **??**), respectively discussed below[4]

### *4.1. November 2007 to February 2010*

### *4.2. August 2015 to July 2017*

The last five months of 2015 was characterised by extreme political volatility in South Africa. The period started out with uncertainty about the Monetary Policy Committee's (MPC) decision regarding the instrument rate. Amid unfavourable economic conditions such as high unemployment, *Fees must Fall*- and wage inequality strikes and concerns about rising debt levels, it was not sure whether the MPC will increase the repo rate or leave it unchanged. These conditions on their own were also a source of uncertainty as newspapers speculated about the impact of the economic downturn. In this period, the news was also dominated by uncertainty regarding the future of electricity supply in South Africa. In particular, the discussions in parliament regarding the proposed nuclear programme enjoyed extensive coverage in the news.

One big event caused all four indices to show the biggest spike in uncertainty at the end of 2015: the replacement of Minister of Finance Nhlanhla Nene, with a relatively unknown figure, David van Rooyen. This shock came amid already rising concerns for a credit ratings downgrade. The nuclear procurement programme was approved by cabinet shortly after the replacement of Nene as minister. Giving in to mounting pressure from various agents, President Jacob Zuma replaced David van Rooyen with Pravin Gordhan after only four days as finance minister. This went a long way in lowering uncertainty in the subsequent month, but the level of uncertainty remained high for 2016 and 2017 compared to before September 2015.

In 2016, *Fees must Fall* protests continue with the start of the academic year with increased pressure on government to intervene. Regardless, President Zuma's state of the nation address in February 2016 failed to provide certainty about the ruling party's proposed plans to address the dire state of the economy and ongoing protests. Moreover, during the first two months of 2016, there was considerable uncertainty about the future of South Africa's sovereign credit rating as rating agencies kept a close eye on minister Pravin Gordhan delivering the budget speech at the end of February. The finance minister

[3] The calculations show breakpoints for the political uncertainty index at November 2007, February 2010 and August 2015. For the fiscal policy uncertainty index at December 2007, January 2012 and August 2015. For the monetary policy uncertainty index at November 2007 and April 2014. For the financial uncertainty index at December 2007 and July 2014.

[4] For the subsequent sections, numerous newspaper articles in the constructed dataset was consulted to build a chronological narrative of economic policy uncertainty in South Africa. Along with this, various internet sources was consulted to identify the largest news stories, including: South African History Online ("2016 in Review" 2016), BBC News ("South Africa Profile - Timeline" 2018), Mekuto (2017), .

remained in the news the following month with rumours of his arrest resulting from an investigation by the Hawks into a “rogue unit” when he was commissioner at the South African Revenue Services.

The second quarter of 2016 saw the Constitutional Court condemn President Zuma’s handling of the Public Protector Thuli Madonsela’s report on improvements to the president’s private property, Nkandla. The court’s finding increased calls for Zuma’s resignation. The news referred to this time as a *deep political crisis* for the ruling party. Uncertainty ruled about the voting process in a motion of no confidence against the president after the party decided to support Zuma in a meeting of the party’s top six officials. These events had a significant impact on the financial markets with the Rand losing ground against the Dollar and fear of a credit rating downgrade increasing. By the end of the quarter uncertainty decreased (also seen in figures **??** to **??**) with reports about the possibility of a downgrade being less frequent.

In the third quarter of 2016 the political landscape in South Africa seems to calm down. This notwithstanding the municipal elections in August which does not show an increase in the indices to the extent that is seen in the previous quarter. This is likely due to the extensive coverage of the results of the Brexit referendum in the news. In September, President Zuma pays back the money owed according to the Public Protector’s report for the upgrades to Nkandla. Apart from the normal coverage of the MPC’s decision regarding the repo rate, this quarter ends on a considerably less uncertain note.

The end of 2016 was characterised by renewed uncertainty about a looming credit rating downgrade. Early in the final quarter of 2016 multiple reports issued by among other, previous Minister of Finance Trevor Manuel as well as Pravin Gordhan warned against deviating from the fiscal targets set in the February budget. This was amid ongoing investigations into minister Gordhan who was preparing the medium-term budget speech that was sure to play a key part in the ratings agencies’ decision. Despite markets expecting a one notch downgrade, all three rating agencies placed South Africa on a negative outlook for one year. Charges against minister Gordhan were dropped at the end of October.

A second report released by Public Protector Thuli Madonsela at the end of 2016 proved to set the stage for a number of events in 2017. The report concerned President Zuma’s involvement in and the extent of state capture in South Africa. However, the ANC again stood by Zuma calling the report inconclusive.

## 5. Conclusion

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