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. PDFs containing digital scans of articles in three newspapers were downloaded from the Sabinet online database. These files were converted to raw text format using PDFTOOLS. The final dataset comprises 178688 articles in three South African newspapers from January 2004 till October 2017. The *Business Day* newspaper constitutes the largest contribution with 117169 articles, the *Sowetan* 37403 articles and the *Financial Mail* the remaining 24116 articles.

These newspapers represent a large readership throughout South Africa. The *Sowetan* is by far the biggest newspaper out of the three, having an exclusive readership of around 500 000. The *Business Day* can be considered the most read newspaper aimed at financial matters and has a readership of approximately 80 000. The smallest of the three, the *Financial Mail*, is a very concentrated newspaper with a key focus in the financial, investment and political space. It's readership hovers around 40 000. All of these newspaper fall under a publishing house called the Tiso Blackstar Group which specialises in print and digital media products.

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.

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 index.

4. The evolution of Economic Policy Uncertainty in South Africa

5. Conclusion

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

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