Constructing Noise Free Economic Policy Uncertainty Index

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ABSTRACT

The economic policy uncertainty (EPU) index is one of the important text-based indexes in finance and economics fields. The EPU indexes of more than 26 countries have been constructed to reflect the policy uncertainty on country-level economic environments and serve as an important economic leading indicator. The EPU indexes are calculated based on the number of news articles with some manually-selected keywords related to *economic*, *uncertainty*, and *policy*. We find that the keyword-based EPU indexes contain noise, which will influence their explainability and predictability. In our experimental dataset, over 40% of news articles with the selected keywords are not related to the EPU. Instead of using keywords only, our proposed models take contextual information into account and get good performance on identifying the articles unrelated to EPU. The noise free EPU index performs better than the keyword-based EPU index in both explainability and predictability.

CCS CONCEPTS

• **Information systems → Data cleaning**.

KEYWORDS

Economic policy uncertainty, document filtering, denoise, economic index

ACM Reference Format:
Chung-Chi Chen, Hen-Hsen Huang, Yu-Lieh Huang, and Hsin-Hsi Chen. 2021. Constructing Noise Free Economic Policy Uncertainty Index. In *Proceedings of the 30th ACM International Conference on Information and Knowledge Management (CIKM '21), November 1–5, 2021, Virtual Event, QLD, Australia.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3459637.3482075

CIKM '21, November 1–5, 2021, Virtual Event, QLD, Australia

ACM ISBN 978-1-4503-8446-9/21/11…$15.00
https://doi.org/10.1145/3459637.3482075

1 INTRODUCTION

News is one widely retrieved textual data that is taken as information source in various application scenarios. In the financial domain, many indexes calculated based on daily news articles are shown to have a high correlation to the real-world economics [3, 19]. The economic policy uncertainty (EPU) index [3] is a famous one. Baker et al. [3] propose three keyword sets to match the mentions of *economic*, *uncertainty*, and *policy* in news articles. The keyword set for *economic* consists of "economic" and "economy", the set for *uncertainty* consists of "uncertain" and "uncertainty", and the set for *policy* consists of "Congress", "deficit", "Federal Reserve", "legislation", "regulation", and "White House". Every month, they calculate the number of news articles containing at least one keyword in every keyword set. They further show that an index based on this keyword matching approach reflects the EPU of the US. Several works[1] follow this methodology to construct EPU indices for different countries [1, 7] or special economies such as Hong Kong [17]. Although the keyword-based approach is widely used, we find that over 40% of news articles retrieved by this approach are not related to the EPU. Such a kind of noise influences both the explainability and predictability—particularly important for financial applications—of the EPU index toward macroeconomic variables [26]. In this work, we aim to remove these noises for improving the explainability and predictability of EPU index.

We remove the unrelated articles, and construct a noise free economic policy uncertainty index based on these pruned news articles. Then, we estimate the explainability and predictability of the original EPU index and the proposed noise free EPU index toward macroeconomic variables, including the Consumer Price Index (CPI), the Industrial Production Index (IPI), and the market volatility index (VIX), and find that the noise free EPU index outperforms the original EPU index in both aspects. Additionally, we also provide a correlation analysis among the EPU indexes of different countries. Our results show that the proposed noise free EPU index can reflect the domestic information better than the original EPU index, which may be influenced by the noise from global information.

The contributions of this work are threefold as follows.

[1] https://www.policyuncertainty.com/

Table 1: Keywords used for EPU indexes of USA and China.

Economic Terms	Uncertainty Terms	Policy Terms			
United States & China	United States & China	United States		China	
economic economy	unceretainty uncertain	congress white house	regulation federal reserve	China Beijing	interest rates People's Bank of China

(1) We point out and remedy the shortcomings of the keyword-based economic indexes.
(2) We integrate the advantages of the keyword-based method and context-aware method, and propose a high-accurate denoising method.
(3) Our results show that the proposed noise free EPU index can better reflect the real-world economic environment.

2 PRIOR KNOWLEDGE

2.1 Construction of EPU Index

EPU has long been a focus in the economic domain [4, 18]. This kind of uncertainty influences the decisions of households [13, 14], firms [5, 6, 25], and enterprises [9, 20]. Baker et al. [3] propose a keyword-based method for evaluating the EPU using daily US news. Some works [2, 27] follow their method to construct the EPU index for different countries. However, we find that this kind of keyword-based method may retrieve noisy information, which will reduce both the explainability and predictability of the constructed indices. To the best of our knowledge, no previous work explores the issue of noise reduction in the EPU index.

Table 1 lists the keywords used for constructing EPU index for USA and China. There are three groups of keywords, including economic terms, uncertainty terms, and policy terms. These keywords are selected based on researchers' experience. From Table 1, we can find that the policy terms are very different among countries. For example, "white house" and "Beijing" are the specific terms used for these countries, respectively.

The first step of constructing the EPU index is to count the number of news articles (N_{EPU}) containing at least one keyword in each group monthly. Thus, the raw EPU index (EPU_{Raw}) is calculated based on Equation 1.

$$EPU_{Raw} = \frac{N_{EPU}}{N_{All}} \tag{1}$$

where N_{All} is the total number of news articles published in a month. After we get monthly EPU_{Raw}, the second step is to standardize and normalize the series [3]. The resulting series in previous work is called the original EPU index hereafter.

2.2 Noise in the Keyword-based EPU Index

Most of the terms listed in Table 1 are general terms. Despite some country-specific terms in the policy keyword group, many articles related to the EPU of other countries will also be retrieved by the general terms such as "regulation", "interest rates", and "authorities" for the target country using the pure keyword-based method specified in Section 2.1. That will influence EPU_{Raw}. For example, the article entitled "Latvian civil servants fired, salaries cut" and "Brazil rescues economy – 2 trillion foundation established" is related to the EPU of Latvian and Brazil, instead of the United States. This kind of articles will be wrongly counted when calculating the EPU index of the United States.

Similar cases occur quite often in the retrieval process. For instance, the article entitled "Quarterly report disappoints – sell Epistar Corp." mentions poor macroeconomic policies as the cause of the company's declining profits. This kind of news relates only to the mentioned companies but not to the country-level EPU directly. Another example is the article about the poor, such as the article titled "Sick wife and intellectually disabled child – husband hopes to find employment". This kind of articles also contains the listed keywords in Table 1. In this paper, we probe the influence of such a kind of noise and show that we can make the the EPU index more reliable after the denoising process.

3 CONSTRUCTION OF NOISE FREE EPU INDEX

3.1 Experimental Dataset

Pure keyword search with economic terms, uncertainty terms and policy terms will retrieve many unrelated news articles, thus an incorrect EPU index is computed. To examine the effects from noise and the performance of denoising model, we prepare an experimental dataset. Data are collected from four major newspapers—Commercial Times, China Times, Liberty Times, and Apple Daily—in Taiwan from May 1, 2003 to June 30, 2018. We use the keyword sets listed in Huang et al. [15] to sort out the target news, resulting a total of 47,171 news articles with these keywords. Each article contains at least one keyword in the economic keyword set, the policy keyword set, and the uncertainty keyword set. All the retrieved articles are labeled by experts in the economic domain as either EPU-related or noise. This yields 27,800 EPU-related news articles and 19,371 noisy news articles in our dataset. The noisy news articles account for 41% of the total. To check the agreement between annotators, we randomly select 2,000 instances and ask them to label this subset. The Cohen's kappa agreement [10] is 81.70%. Finally, we separate the dataset by time into training set, development set, and test set with 80%, 10%, and 10%, respectively.

3.2 Identifying Unrelated Articles

By observing the unrelated news articles labeled by annotators, we notice the following phenomena:

- The news title contains the main idea of the news article. In many instances, we can identify whether the given news is related to the EPU index by reading through the headline.
- We find that the text span around the EPU keywords provides much information. For example, the sentence "8 life

Table 2: Experimental results. The underlined numbers indicate the best performance when using the same architecture, and the bold numbers indicate the best performance in this experiment.

Model	Input Data	Micro-F1	Macro-F1
CNN	Title	<u>82.57%</u>	<u>81.54%</u>
	Article	80.92%	79.48%
	Text Span	82.51%	81.31%
BiGRU	Title	82.59%	81.46%
	Article	83.19%	82.47%
	Text Span	<u>83.93%</u>	<u>83.10%</u>
CapsNet	Title	<u>81.92%</u>	<u>81.07%</u>
	Article	81.39%	80.28%
	Text Span	81.03%	79.57%
BERT	Title	87.94%	87.69%
	Article	88.62%	88.31%
	Text Span	**<u>89.57%</u>**	**<u>89.38%</u>**

Table 3: Experimental results with multiple input.

Model	Data	Micro-F1	Macro-F1
BiGRU	Title + Article	83.50%	82.31%
	Title + Text Span	<u>85.41%</u>	<u>84.42%</u>
BERT	Title + Article	89.76%	89.48%
	Title + Text Span	**<u>90.74%</u>**	**<u>90.45%</u>**

insurance companies announced in June that **interest rates** remain unchanged" contains the policy term "interest rates". If we use not only the keyword, but also the complete sentence containing the keyword, we can easily understand that this sentence is not related to the policy uncertainty.

- The mentioned country name in the news article is helpful for identifying whether this news discusses the economic events of the target country. For example, the news mentioned Brazil should not be selected when we calculate the EPU index of the USA.

Based on these findings, we adopt the combination of the title and the text span around the EPU keywords to identify unrelated articles. We compare the performances of convolutional neural networks (CNNs) [16], bidirectional gated recurrent units (BiGRU) [8], capsule networks (CapsNets) [23], and BERT [11]. Table 2 shows the experimental results. The BERT architecture with text spans performs the best in these experiments. When CNN and CapsNet are considered, using title as model input performs the best. When BiGRU and BERT are considered, using the text span as model input get the best performance. These results echo our findings during annotation—the text span among the EPU keywords is informative for identifying the unrelated articles.

Because different parts in an article contain different information, we further show the experimental results with multiple input in Table 3. Given the good performances of BiGRU and BERT architectures in the experiments in Table 2, we explore both models in this experiment. The experimental results show that using both title and text span as model input performs better than using title and article directly. The results in Table 2 and Table 3 support the usefulness of the text span containing the EPU keywords for denoising.

We further propose a simple but practical method to consider the country name during denoising. Inspired by Raffel et al. [21], which adds a simple tag in the front of input to deliver the question type to the model, we add a tag for the geography information of the news article in the front of input. We construct a list containing 390 Taiwan domestic region names, 198 international country names, and 623 international county names. We use the following tags.

- "[Global]" if there exist at least one domestic region name and at least one international country/county name in the news articles.
- "[Taiwan]" if there exist at least one domestic region name and none of the international country/county names in the news articles.
- "[International]" if there exist at least one international country/county name and none of the domestic region names in the news articles.
- "[Unknown]" if there are not any country/county names in the news articles.

We find that adding geography information is helpful for reducing both Type I (-1.14%) and Type II (-1.05%) errors.

3.3 Construction Process

We introduce the process of the construction of the noise free EPU index as follows. First, we collect the news articles that contain at least one keyword in each group as the first step of the original EPU index in Section 2.1. Second, we check each collected news article by the proposed denoising model in Section 3.2. Third, we only count the retrieved articles by the model when calculating N_{EPU} in Equation 1. Forth, we perform the same standardized and normalized approaches as constructing the original EPU index.

4 IMPROVEMENTS AFTER DENOISING

4.1 Explainability and Predictability

Regression analysis, commonly utilized in empirical finance, not only estimates the predictability of the economic index, but also evaluates the explainability [26]. We use regression analysis to estimate the explainability and predictability of the EPU index toward the growth rate of three macroeconomic variables, including the Consumer Price Index (CPI), the Industrial Production Index (IPI), and VIX Index (VIX). The estimations are based on the following time series model of previous work [24]:

$$y_t = \beta EPU_t + \sum_{i=0}^{2} \alpha_i y_{t-i} + \alpha + \epsilon_t \,, \tag{2}$$

where y denotes the target macroeconomic variable, and t denotes the period t. We further evaluate the influence on predictability

Table 4: Estimations of Explainability and Predictability. p**-values are calculated by t-test. ↑↑: p < 0.01, and ↑: p < 0.05.**

	Explainability		Predictability	
	Original	Noise Free	Original	Noise Free
CPI	↑↑	↑↑	-	↑
IPI	-	↑↑	-	↑↑
VIX	↑↑	↑↑	-	↑

with the following equation:

$$y_{t+1} = \beta EPU_t + \sum_{i=0}^{2} \alpha_i y_{t-i} + \alpha + \epsilon_{t+1} \tag{3}$$

Table 4 shows the analysis of explainability and predictability. We find that the original EPU index does not have statistically significant explainability toward IPI, but the proposed noise free EPU index does. The estimation on predictability provides more exciting results toward predictability. The original EPU index does not provide statistically significant predictability toward all macroeconomic variables. After denoising, the proposed noise free EPU index becomes a good index for predicting the growth rate of all macroeconomic variables.

4.2 Connectedness among Different EPU Indexes

To evaluate whether the proposed noise free EPU index succeeds in removing unrelated international news such as the news related to Brazil shown in Section 2.2, we perform the connectedness analysis [12]. The notion of connectedness analysis is that we evaluate the correlation between Taiwan's EPU index (both original EPU and noise free EPU) and the EPU indexes of other countries. Because the EPU index should reflect the uncertainty of domestic economic policies, it should not have a high correlation with the EPU indexes of other countries. The evaluation method of Diebold and Yılmaz [12] provides the directed connectedness analysis results. That is, we can evaluate the connectedness from other countries' EPU indexes to Taiwan's EPU index.

Table 5 shows the connectedness table. Note that, based on the abovementioned rationales, the correlation shown in this table is the lower, the better. We not only analyze the correlation with the representative countries/economies (USA, China, and UK), but also provide the analysis of the near countries/economies (Korea, Hong Kong, and Singapore) of Taiwan. These results show that the proposed noise free EPU index successfully reduces the noise from other countries' economic policies.

Table 5: Connectedness Table.

Representative Countries				
	From	USA	China	UK
To	Original EPU	9.26	7.30	2.69
	Noise Free EPU	**7.43**	**2.48**	**1.42**
Near Countries				
	From	Korea	HK	Singapore
To	Original EPU	7.77	10.08	11.05
	Noise Free EPU	**6.84**	**9.19**	**7.76**

5 RELATED WORK

With the development of computational infrastructure, dealing with a bunch of documents becomes possible. More and more researchers in other domains start to investigate how to apply the technologies in AI or information retrieval to their studies. The EPU index discussed in this paper is one of the instances in economics and finance. Based on our observation, many recent studies in economics and finance fields are still using traditional methods such as keyword-based approach [1, 3, 7, 17] and topic model [22] to retrieve the related documents for further analysis. Although these studies provide positive results when analyzing their indexes, they may underestimate or overestimate their results due to the noise included in their indexes. In this work, we provide an exploration to show that the widely-used keyword-based method includes much noise when constructing EPU index. We point out several possible issues that need to be taken into consideration when using the keyword-based method. Our experimental results show that with the help of current state-of-the-art models in the NLP field, we can get a better EPU index. To the best of our knowledge, this is one pioneering work in this direction.

6 CONCLUSION

In this paper, we propose a noise free economic policy uncertainty index by addressing the shortcomings of previous works. We add a denoising step in the construction process for removing the news articles unrelated to economic policy uncertainty. We further show that the noise free EPU index constructed based on the proposed process performs better than the original EPU index in several aspects. Our findings can lead future work to rethink whether the keyword-based economic index truly presents the information in the real-world economic environment, and how to construct a better textual-based index.

Because the keyword groups of different countries are selected manually, and the terms may vary from different countries, especially the policy terms, an automatic method is needed for choosing the keywords for constructing an EPU index for a new target or for choosing the news articles related to new economic policy. We plan to find a solution to this issue in the future.

ACKNOWLEDGMENTS

This research was partially supported by Ministry of Science and Technology, Taiwan, under grants MOST 109-2218-E-009-014, MOST 110-2634-F-002-028, and MOST 110-2221-E-002 -128 -MY3. It was also financially supported by the Center for Research in Econometric Theory and Applications (Grant no. 110L900202) from The Featured Areas Research Center Program within the framework of the Higher Education Sprout Project by the Ministry of Education (MOE) in Taiwan, and by the Ministry of Science and Technology (MOST), Taiwan, under Grant No. 110-2634-F-002-045.

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